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The relationship between heating energy use, indoor temperature and heating energy demand under reference conditions in residential buildings

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ABSTRACT

This thesis started by characterizing the thermal performance of the residential building stock in Portugal mainland and by performing a preliminary assessment of the 'reference heating gap' of the stock, using the Portuguese EPBD-derived EPC database.

The second research topic concerned the characterization and prediction of indoor temperatures during the winter season, in the residential buildings in Northern Portugal. The work was based on the monitoring campaign carried out at Porto, Ponte de Lima, Bragança and Sabrosa for the winter season period of 2013-14. Models, particularly effective at predicting bedroom and the living room temperatures, were developed using linear regression with panel corrected standard errors.

The last major topic was the development of statistical models to characterize the relationship between heating energy use, indoor temperatures and heating energy demand under reference conditions (HDRC) (i.e., values from energy rating/certification scheme´s databases) in the residential buildings. These models are applied to Portugal and to different geographical contexts. The developed models, along with data and assumptions from the previous chapters, assisted the assessment of the value of 'heating gap' of the residential building stock in Portugal mainland. It was found that the actual energy use for heating is only about 45% of that occupants would need to maintain a comfortable environment.

Motivated by the lack of buildings data, this thesis also focuses on the potential use of energy rating/certification schemes´ databases, as a rich and available source of data for countries´ decision-making and future energy planning. The results of the models proposed will be of outmost interest for the development of energy planning practices regarding the residential building stock.

RESUMO

Esta dissertação começou por caracterizar o desempenho térmico dos edifícios residenciais em Portugal Continental e por realizar uma avaliação preliminar do 'gap de referência de aquecimento’ do parque imobiliário, usando a base de dados do Regulamento Energético Português derivado da Diretiva EPBD.

O segundo tema de investigação estudou a caracterização e previsão de temperaturas interiores durante o período de inverno, nos edifícios residenciais no norte de Portugal. O trabalho baseou-se na campanha de monitorização realizada no Porto, Ponte de Lima, Bragança e Sabrosa no período de estação de Inverno de 2013-14. Modelos, particularmente eficazes na previsão das temperaturas interiores dos quartos e salas, foram desenvolvidas por meio de regressão linear.

O último tema desenvolveu modelos estatísticos que caracterizam a relação entre o uso de energia para aquecimento, as temperaturas interiores e o valor teórico das necessidades de energia para aquecimento calculado sob condições de referência (HDRC), (i.e., valor proveniente das bases de dados de regulamentos de certificação energética), nos edifícios residenciais. Estes modelos são aplicados ao parque imobiliário residencial português e em contextos geográficos diferentes. Os modelos desenvolvidos, juntamente com dados e pressupostos dos capítulos anteriores, auxiliaram a avaliação do novo valor do 'gap de aquecimento' do parque imobiliário residencial em Portugal Continental. Verificou-se que a energia atual usada para aquecimento é cerca de 45% da necessária para se manter um ambiente confortável.

Motivada pela falta de dados sobre o edificado, esta dissertação foca-se também no potencial do uso das bases de dados dos regulamentos de certificação energética, como uma fonte de dados rica e disponível para a tomada de decisão e planeamento energético futuro. Os resultados dos modelos propostos serão de grande interesse para o desenvolvimento de práticas de planeamento energético em relação ao edificado residencial.

LIST OF ABBREVIATIONS

1F	Apartment with one external facade
2F	Apartment with two external facades
3F	Apartment with three external facades
A1	Approach 1
A2	Approach 2
AEU	Actual energy use [kWh/m^2.year]
ADENE	Portuguese Agency of Energy
A.F.	Absolute frequency
ANN	Artificial Neural Network
ANSI	American National Standards Institute
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
ATH	Always at home
BREDEM	British Research Establishment´s Domestic Energy Model
BREHOMES	Building Research Establishment´s Housing Model for Energy Studies
CA1	Only in common area in the period 1
CA2	Only in common area in the period 2
CA3	Only in common area in the period 3
CDRC	Cooling energy demand under reference conditions [kWh/m^2.year]
CFC	Complex Fenestration Construction
CREEM	Canadian Residential Energy End-use Model
DGEG	General Directorate of Energy and Geology
DHW	Domestic hot water
DWDRC	Domestic hot water under reference conditions [kWh/m^2.year]
EA	Everywhere, anytime
EO1	Everywhere in the occupied period 1
EO2	Everywhere in the occupied period 2
EPB	Energy Performance Buildings
EPBD	Energy Performance Buildings Directive

EPC	Energy Performance Certificates
GLSedit	Glazing shading layer editor
HA%	Percentage of heated area [%]
$HA\%_{ref.}$	Reference percentage of heated area [%]
HDD	Heating degree days
HDRC	Heating energy demand under reference conditions [kWh/m^2.year]
$HDRC_{RCCTE}$	Heating energy demand under RCTTE reference conditions [kWh/m^2.year]
$HDRC_{REH}$	Heating energy demand under REH reference conditions [kWh/m^2.year]
$HDRC_{st}$	Heating energy demand under standard reference conditions [kWh/m^2.year]
HEU	Heating energy use [kWh/m^2.year]
HG	Indoor heat gains [W/m^2]
HG_{ref}	Reference indoor heat gains [W/m^2]
HP	Heating period
HPat	Heating pattern
$HPat_{ref}$	Reference heating pattern
HP_{ref}	Reference heating period
HVAC	Heating Ventilation and Air Conditioning
INE	National Institute of Statistics
IR	Air infiltration rate/natural ventilation [ac/h]
IR_{ref}	Reference air infiltration rate/natural ventilation [ac/h]
LW	Layer weight
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error [%]
MLR	Multivariate Linear Regression
MNLR	Multivariate Non-Linear Regression
MSE	Minimum Square Error
MTO	Morning time out
N.A.	Not applicable
OOB	Occupancy and occupant behaviour characteristics
PAA	Portuguese Agency of Environment
PDRC	Primary energy demand under reference conditions [kWh/m^2.year]
PMV	Predicted Mean Vote
PPD	Predicted Percentage Dissatisfied [%]
PV	Photovoltaic
R^2	Coefficient of determination

R.B.S	Residential Building Stock
RCCTE	Regulation of the characteristics of thermal behaviour of buildings
REH	Regulation of the thermal performance of the residential buildings
R.F.	Relative frequency [%]
RMSE	Root Mean Square error [%]
RSECE	Regulation for Building Energy Systems and HVAC of buildings
Sig	Significance
SP	Specific period
THD	Theoretical heating energy demand [kWh/m^2.year]
$THD_{r.t.c.c.}$	Theoretical heating energy demand under relaxed thermal comfort conditions [kWh/m^2.year]
$THD_{s.t.c.c.}$	Theoretical heating energy demand under stringent thermal comfort conditions [kWh/m^2.year]
TRF	Total relative frequency [%]
Tsp	Set point temperature [ºC]
Tsp_{ref}	Reference set point temperature [ºC]
W2	When and where occupied
WHO	World health organization
WTO	Work time out

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CHAPTER 1

INTRODUCTION

1.1 General context

The energy policy context since the beginning of the XXI century requires a strong incentive towards energy demand-side management and energy efficiency. The buildings sector is, along with transports and renewable energy, a key area of intervention. This happens because it accounts for 35% of the world final energy use [1], and also because it is recognized as one of the sectors where carbon abatement can be achieved with lower costs. Among the various energy uses in buildings in developed countries, heating represents about 45% of the total energy use.

Properly designed buildings, in view of their local climatic conditions, can lead to drastically moderate or reduce final energy demand for comfort (e.g. heating, cooling, ventilation, and lighting energy services) [2] as a result of careful implementation of what is sometimes called as 'sufficiency' strategies [2–4]. The sufficiency strategies give the building, as an 'energy system', the ability to catch and manage ambient energy for the purposes of comfort, resorting to external insulation of walls, thermal inertia of the internal walls, orientation and sizing of openings, shading of the glazed surfaces, etc. In this way, the design of a building can pre-empt part or all of the energy demand for comfort with little need for 'add-on' energy systems. If still 'add-on' systems are required, energy-efficiency concerns [2] are applicable to reduce the energy use to generate the energy service [4].

Because of the innumerous non-technological solutions (sufficiency strategies), at the level of the building operation and envelope, designed to reduce the extent of energy services needed to maintain the required comfort level in a building [4], and because of the technological solutions that are designed to provide energy services at lower levels of energy use (energy efficiency measures) [4], the building sector has been receiving especial attention from policy makers [5–7].

In what regards heating, there is awareness that indoor thermal comfort for a significant number of existing dwellings worldwide is not yet guaranteed. Several studies in the literature point out that indoor temperatures in winter, in many dwellings, are kept below the levels usually deemed as comfortable, and in many cases, even below the recommended levels [8–16].

It is known that at least in some European countries this reality is associated, in part, with the poor building construction in terms of 'sufficiency' and/or the lack of efficient central heating systems [17,18]. For these reasons, this problematic is often named as 'cold homes' [14,17,19].

The issue is that, supposing unmet thermal comfort needs is a reality, in the long term, it could have particular influence on the performance outcome of existing building renovation and/or energy efficiency programmes. This happens because these programmes are normally designed assuming reference indoor temperatures/heating patterns that are usually not accurate. It has been widely reported that thermal upgrades, more energy efficient heating systems and better controls, especially in homes which are operated at low indoor temperatures, do not always save as much energy as predicted [20–22] and can lead to unintended consequences [23]. Actually, it might happen that occupant´s thermal comfort expectations get more demanding with the upgrades. For example, Critchley *et al.* [14], in their study of the impact of Warm-Front efficiency programme, registered occupants reporting ''I have never been used to heating upstairs'' and ''I noticed the difference (after efficiency measures) though I might have thought differently before I had central heating". This type of behavioural response to improvements, which leads to shortfall in expected energy savings as a trade-off for warmer temperatures, is a form of the so-called 'rebound effect' [24–29].

The register of indoor temperatures lower than those needed for comfort may also represent a potential for future increase in heating energy demand, if the economic conditions improve in the mid-term future; the energy prices go down; and/or there is a demand for higher thermal comfort levels (i.e., increase of thermal comfort expectations).

Hereupon, both for energy and health policies, understanding in detail the actual indoor temperatures, the heating patterns, as well as the unmet thermal comfort needs of existing residential buildings, is fundamental as they may give some indication on what to expect regarding the evolution of the energy use for heating, and influence the design of energy and climate plans, as well as the design of new dwellings and refurbishment of existing ones.

1.2 Motivation and research objectives

There are two approaches that can provide with an indication of whether or not occupants feel comfortable within their indoor environmental conditions. These are the characterization of indoor temperatures (by evaluating if they are within the commonly recommended values) and the evaluation of the perception of thermal comfort of the occupants to their indoor environment [13,30–51]. But, the comparison between the '*theoretical heating energy demand under (ensuring) thermal comfort condition*s' and the '*actual energy use'* for heating, of the residential building stock, can be a useful exercise to assess whether the thermal comfort needs are truly being met.

This makes place for the concept of energy use gap, defined as the amount of additional heating that would be needed to ensure that buildings were maintained at comfortable indoor temperatures, in their current physical state.

At this stage it is important to recall that this theoretical concept of energy use gap does not apply when the occupants are satisfied with their thermal comfort environment. Also, somehow related to social aspects of thermal comfort expectations, the exercise of the estimation of energy use gap is a challenging one. The estimation of the theoretical value for the entire residential building stock is difficult because the levels of thermal comfort are usually unknown, dependent on each occupant and subjected to changes over time and with age.

When aiming at determining the '*theoretical heating energy demand (THD) under thermal comfort conditions*' of the residential building stock, one faces several possibilities. At the uppermost extreme of these is to assume that all indoor space needs to be maintained at a certain temperature during all the winter/heating season period (e.g. at 20ºC or 18ºC) to ensure comfort indoor environments. This is an assumption often found in energy rating/certification schemes such as those in place after the Energy Performance Buildings Directive (EPBD) and it is usually named as reference conditions. However, more relaxed/reasonable values will probably be achieved if it is taken into account that occupants do not need to heat homes during all time, and not all rooms at the same temperature, and even not the same temperature at all time (e.g. comfort during sleep can be achieved at lower temperatures than during active hours [52]): i.e., assuming more relaxed values for thermal comfort conditions.

This leaves two possible but different situations of estimating the 'THD under thermal comfort conditions'. When the estimation of THD assumes more relaxed levels of thermal comfort conditions, the energy use gap is designated as 'heating gap'. In turn, when the THD assumes stringent thermal comfort conditions, i.e., when theoretical heating energy demand under reference conditions (HDRC) values, provided, for example, by energy ratings/certifications schemes, are used as direct values of thermal comfort conditions, the computed energy use gap is called as 'reference heating gap'.

Figure 1 illustrates the two variants of the energy use gap that are introduced in this thesis in the context of the residential building stock.

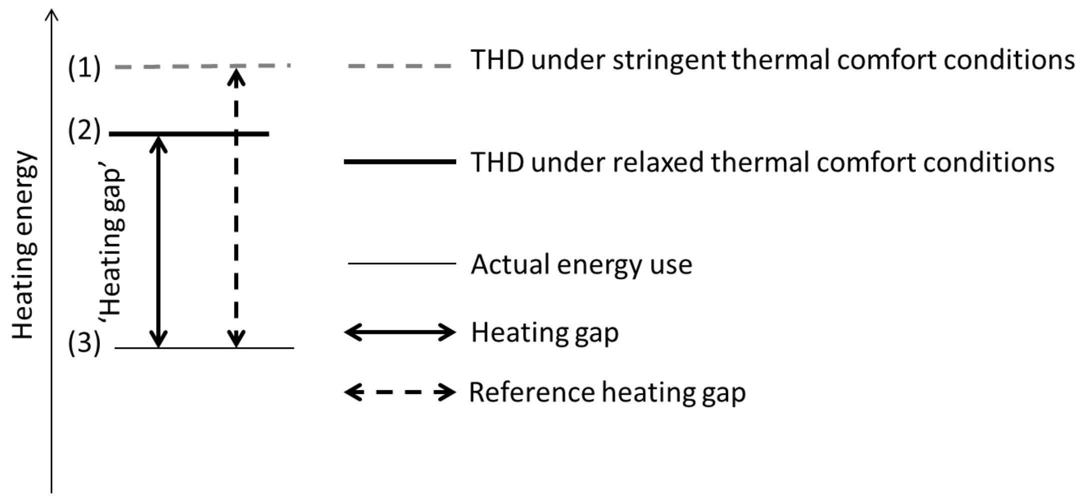

Figure 1. Schematic illustration of the different levels of heating energy and the 'heating gap' and 'reference heating gap' of the residential building stock.

‘Heating gap’ is the difference between *(2)* and *(3),* in Figure 1, and ‘reference heating gap’, the difference between *(1)* and *(3),* in Figure 1.

Currently, there are several energy ratings/certifications schemes in force worldwide and these hold extensive energy performance certificates´ (EPC) databases ready to be exploited. Actually, motivated by the lack of building data, one can think that the estimation of the ‘*THD under thermal comfort conditions’* of the residential building stocks can be assisted with those databases, provided that they contain HDRC values.

Based on recent literature findings [53–59] the EPBD-derived EPC databases emerge as a good example of application for the European context. The European Commission has put forward the EPBD directive (2002/91/EC) in 2002 [6]. This Directive was enacted for labelling the energy performance improving the energetic quality of new buildings and existing building stocks. A subsequent update under directive 2010/31/EC [7] (the EPBD recast) set more demanding objectives, such as the nearly net-zero energy building. The implementation of the EPBD 2002/91/EC with the attribution of energy performance certificates (EPC) to almost all buildings in Europe has therefore somehow initiated the mapping of thermal performance of the existing European building stock [60]. The EPBD-derived EPC databases compile a great number of energy performance certificates, which have been issued both for new and existent[1] buildings. Each certificate provides a theoretical HDRC value, for each building [61].

The computation methodologies require a number of operating conditions to be defined, such as building’s density of occupation, set point temperature, occupancy profiles and operational schedules of building services. These operating conditions (i.e., occupant behaviour), along with other physical building parameters, are often unknown in the design of new buildings or subject to a lot of uncertainty in existing buildings. This justifies the use of values assuming reference conditions under the EPBD, or under any other energy rating/certification scheme.

Even if the purpose of EPBD methodology is mostly to ensure compliance with Building Regulations [62], and even though some thoughts regarding the need for improvements to the

[1]Only required when there is a commercial transaction.

EPBD approach are pointed out by [2], the HDRC values can still serve as direct values for the THD needed to ensure thermal comfort conditions of the residential building stock, although aligned with the stringent perspective of thermal comfort (*(1)* in Figure 1).

Furthermore, studies have shown that occupant behaviour might play a prominent role in the variation in energy use in different households [63]. It is also recognized that the operating conditions may vary from the standard/reference conditions assumed normally in energy models. In this line, HDRC values could also serve as basis for estimating *heating energy use*, incorporating relaxations on intensity of the heating, providing that there is an understanding of the relationship between the *heating energy use*, *occupant behavior* (e.g. indoor temperatures) and *HDRC*. Using this relationship, the 'THD relaxed thermal comfort conditions' (*(2)* in Figure 1), along with other theoretical heating energy values for different levels of occupant behaviour, can be estimated.

An advantage of this relationship regards its use in the design of energy plans and policies for the entire building stock level. Moreover, besides the abundance of HDRC values and its wide applicability at building stock level, it may be of significant interest to the owners and occupants of residential buildings. Many of these often perceive the energy certificate that they receive as a bureaucratic document whose information has little relationship with reality [64]. A better characterization of the aforementioned relationship could help users to understand the performance of their building fractions[2] in terms of indoor temperature and more realistic heating energy use. This could also be of interest to public health authorities, at a time when most European countries are expected to face a considerable increase in the share or old, and therefore, more vulnerable, population.

[2]Usually referred as autonomous fractions.

The main purpose of this thesis is to develop a model that predicts **heating energy use**, based on the relationship between ***heating energy use***, ***indoor temperatures*** and the theoretical ***heating energy demand under reference conditions (HDRC)***. It involves the development of models applied to different geographical contexts, all applicable at levels of the individual building and of the residential building stock as a whole. Based on the same relationship, models that predict the minimal guaranteed **indoor temperature** in spaces when heated will be equally developed.

Other relevant purposes of this thesis are driven by the hypothesis that there could be occupants living in dwellings in Portugal subjected to poor indoor environment conditions during the winter season. These are: 1) the assessment of the energy use gap and 2) the characterization of indoor temperatures for the Portuguese context. The first, aiming just to attempt to evaluate the existence of the gap and to provide with an indication value, is carried out in two variants, one with raw stringent data ('reference heating gap') and the other with more accurate data (´heating gap´). Being in an European context, this thesis focuses on the EPBD-derived EPC databases, more precisely the Portuguese one, to extract the HDRC values. The characterization of indoor temperatures can be used to support or not the evidence of energy use gap.

The specific objectives of the research are the following:

1) *to perform an assessment of the 'reference heating gap' and a characterization of the thermal performance in the Portugal mainland residential building stock using the EPBD-derived EPC database;*

2) *to characterize the actual indoor temperatures and to understand the heating patterns in the residential buildings in Northern Portugal during the winter season, as well as, to predict indoor temperatures and identify its main determinants;*

3) *to model heating energy use or indoor temperatures in the residential buildings using the relationship between heating energy use, indoor temperatures and HDRC;*

4) *to estimate the 'heating gap' of the residential building stock in Portugal mainland aided by the heating energy use predicting models and EPBD-derived EPC database.*

The outcomes of this thesis will be of outmost interest for the development of energy planning practices regarding the residential building stock. Also, motivated by the lack of building´s data, this thesis focuses on the potential use of energy rating/certification schemes´ databases, as a rich and available source of data for countries´ decision-making and future energy planning.

1.3 Thesis structure

This thesis is divided in six chapters which can be synthesized as follows.

Chapter 1 introduces firstly the problematic behind this research thesis, followed by its motivation and research objectives. Finally, briefly describes the thesis structure.

Chapter 2 starts by presenting a literature review on the assessment of 'heating gap' and 'reference heating gap' of the residential building stock. It presents a review on the characterization of indoor temperatures and heating patterns, and it finishes with a review on how to model heating energy use.

Chapter 3 first characterizes the thermal performance of the residential building stock in Portugal mainland, through the disaggregation of the stock by thermal performance levels, the evolution of the thermal performance over time and the hypothetical effects of regulations. The procedure started by analyzing the collection of the certification poll from the Portuguese EPBD-derived EPC database; and by extracting the theoretical evaluation values from each certificate and the features of the building itself, such as, the construction period, floor area, number of bedrooms and thermal performance class. It followed recent works on the impact of the last European Directive and the resultant energy certification systems [60,65,66].

Chapter 3 also performs a preliminary assessment of the 'reference heating gap' of the residential building stock in Portugal mainland. This procedure also benefited from the collection of HDRC values from the EPC database, which were used as direct values for 'THD under thermal comfort conditions' (i.e., the THD_{stcc}) (*(1)* in Figure 1). These values were extrapolated to the entire residential building stock. The bottom-up assessment was then compared with a top-down assessment of the 'actual energy use' for heating (*(3)* in Figure 1), obtained through the breakdown of the national energy balance to give the 'reference heating gap' of the residential building stock for Portugal mainland. This procedure followed, therefore, other studies focused on the residential building stock found in literature, such as [59,67].

Chapter 4 presents, firstly, the work developed on the characterization of indoor temperatures and heating patterns based on the monitoring campaign carried out during the winter season of 2013-14 at residential buildings in Northern Portugal. Experimental data was gathered from a sample of 141 dwellings monitored in two different rooms (bedrooms and living room). The campaign occurred in four different geographical locations (Porto, Sabrosa, Ponte de Lima and Bragança). The monitoring data was collected at every half hour and was processed on a daily basis for indoor temperature characterization. The heating patterns were identified through the analyses to the mean hourly temperature distribution of each household and the responses to the surveys. It followed work developed on ref. [10]. Secondly, using the collected data during the monitoring campaign, it presents a prediction model of actual indoor temperatures for the Northern residential building stock, identifying its main determinants. This procedure followed ref. [68].

Chapter 5 addresses the development of models to predict heating energy use or indoor temperatures in residential buildings, applied to Portugal (named as Portugal specific models) or to any geographical context (named as universal models). It follows studies developed on statistical models [69–71]. The models with universal applicability were created by applying a statistical model coupled with data resultant from simulations. In this case, the HDRC datasets were obtained from simulations based on reference heating conditions normally assumed in the energy ratings/certification performance schemes, such as EPBD. Statistical models coupled with both simulation and calculation data were performed to develop the Portugal specific models. The Portugal specific models used HDRC values calculated from the Portuguese EPBD regulation´s building energy calculation models [72,73].

This chapter also addresses the assessment of the 'heating gap' for the residential building stock in Portugal mainland, as the estimated value of 'reference heating gap' in chapter 3 used the HDRC values as direct values for THD, values which are likely an excessive standard in terms of thermal comfort requirements. This new assessment was performed differently in a way that 'THD under relaxed thermal comfort conditions' (THD_{rtcc}) (*(2)* in Figure 1) was estimated by applying the HDRC values into the heating energy use predicting models, taking also the advantage of data/assumptions resultant from work developed under chapter 3 and 4.

Finally, chapter 6 first presents the main contributions of the work developed, following its implications for real practice. It ends providing guidelines for future work.

Figure 2 illustrates the relationship between chapters 3, 4 and 5. In particular, the results from estimations undertaken in chapter 3, along with the data/assumptions from the monitoring campaign (chapter 4), contributed to the assessment of the 'heating gap' carried out in chapter 5. This was done through the employment of a predicting model developed in chapter 5. Figure 2 also shows which chapters benefited from the use of Portuguese EPBD-derived EPC database (i.e., chapter 3 and 5). The HDRC values extracted from the EPC database were used to perform the characterization of the thermal performance of the residential building stock of Portugal mainland and the computation of the 'reference heating gap' in chapter 3. The computation of the 'heating gap' was performed applying the HDRC values into a heating energy use predicting model, which was developed under chapter 5.

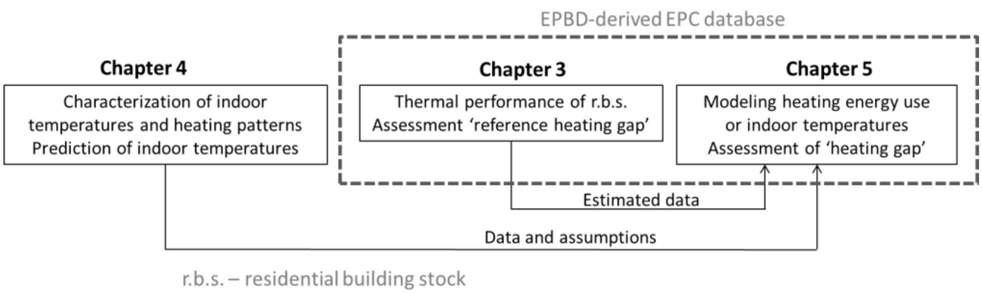

Figure 2. Schematic structure of the connection between the three work packs developed.

CHAPTER 2

LITERATURE REVIEW

The literature review presented in this chapter aims to contextualize the themes of this thesis. It also aims to identify the gaps found in the literature in order to consolidate the objectives and to get better insights concerning the methodological approaches chosen to address those work packs.

This chapter is composed by three sections reviewing the studies related to the main research topics addressed in this thesis. In particular, the first section 2.1 reviews the studies that evaluate the 'heating gap and 'reference heating gap'. The second section 2.2 reviews the studies that characterize indoor temperatures and heating patterns. Section 2.3 focuses on studies aiming to model heating energy use.

2.1 Assessment of 'heating gap' and 'reference heating gap' of residential building stock

Thermal comfort is defined as the 'state of mind that expresses satisfaction with existing environment' [74], making it a subjective concept. Occupants tend to react to external or internal stimulus in order to increase, restore or maintain the comfort conditions (thermal, lighting, acoustics, indoor air quality). In this way, they play a central role in controlling the heating energy use [12,29,47,52,55,63,70,75–81]. In what regards the physical part, thermal comfort may depend on the following environmental variables: mean radiant and air temperature, relative humidity and air velocity [82]. For purposes of large-scale characterization of thermal comfort at home and for health protection guidelines, it is the ambient air temperature that has been the main focus [10,47,83–85]. Levels of comfort with respect to those environmental variables are modified according to clothing insulation and activity level [82], but a further potential influencing factor is considered to be adaptation, which is closely related to experience and expectations of each individual [86–88]. For example, it is argued that the effect of adaptation occurs over time according to outdoor conditions, so that higher indoor temperatures are accepted as comfortable when the outdoor temperature is high, and lower indoor temperatures are accepted as comfortable when the outdoor temperature is low [89,90]. Also, in an empirical study to 600 households in Sweden, Linde´n *et al*. [55] found that those living in detached houses tend to accept lower indoor temperatures than households living in flats. Authors also found that for households living in dwellings where the energy bill is paid collectively the indoor temperature is higher by 2ºC. All these factors may vary according to the members of the household as some occupants may be more susceptible to high or low indoor temperatures than others [83], emphasizing the difference of thermal comfort expectations among occupants.

As presented in section 1.2, the definition of energy use gap is associated with occupants living in indoor environment conditions that may not meet their expected level of thermal comfort. It is estimated by evaluating how much the 'actual energy use' for space heating is lower than the so called '*theoretical heating energy demand (THD) under thermal comfort conditions*'.

Due to the several assumptions and considerations found in literature behind the estimation of THD, it is, at this point, important to recall the fact that, in the estimation of 'heating gap', the THD values regards the demand needed to ensure relaxed thermal comfort conditions (*(2)* in Figure 1, in section 1.2). Also, in the estimation of the 'reference heating gap' it regards the demand needed to ensure stringent thermal comfort conditions ((*3)* in Figure 1, in section 1.2).

Several studies on the gap between the theoretical and the actual measured performance of buildings [62,91] can be found in literature. This comparison is termed as 'performance gap', by some authors [53,54,62,70,91–97] and it matches the concept of 'reference heating gap', introduced in section 1.2, because of the similarities in the methodology of estimation.

However, the 'performance gap' is not estimated with the purpose of determining whether the gap between the 'theoretical' and the 'actual' is part the expression of the difference between reference and actual values for heating patterns (i.e., occupant behavior), or other parameters, or if it is also the expression of a 'deficit of comfort'.

Instead, an expression of the first [91], in particular, differences in the occupant behaviour, is pointed out as the major reason for the 'performance gap'. This is because occupant behaviour plays a central role in controlling heating energy use; and because operating conditions (i.e., occupant behaviour) are normally considered standard/reference rather than actual measured conditions [24,53,54,70,91], which can differ significantly from each other (due to the complex nature of the determinants of occupant behavior [29]).

Indications of the 'performance gap' started to appear from the mid-1990s [98], until nowadays. From the academic literature reviewed [27,92,99,100] on the comparison between theoretical and actual energy use, most of the authors reporting situations where actual energy use is lower than theoretical values estimated the 'performance gap' [53–56,59,70].

From those examples, two actually showed some preoccupations in relation to the future energy savings, which somehow resembles the concept behind the 'reference heating gap'. For example, Sunikka-Blank and Galvin [57] based their study on existing German datasets that included the calculated thermal performance ratings (i.e., energy performance certificates) and the measured energy use data from around 3400 dwellings. They concluded that occupants use, on average, 30% less heating energy than the calculated rating (estimation is done in $kWh/m^2.year$). The authors called this phenomenon as 'prebound effect' and it is referred to the situation before a retrofit, indicating how much less energy is consumed than expected. The authors also considered that the discrepancy suggests less potential for economically feasible savings in Germany's domestic heating energy than assumed, especially because of the correlation between the 'prebound' effect, household income level and energy bills.

Also, Tigchelaar *et al.* [58] in their analysis, from 4700 households in Netherlands, found an identical phenomenon, though they named it the 'heating factor' (average of 0.7). The information used came from a database that was previously obtained through a national survey and compared with the calculated energy performance certificate for each respondent´s home (authors claimed that the figure is representative of the Dutch housing stock for the year of

2006). They suggested that this 'heating factor' severely limits the potential savings through thermal retrofits.

One major observation resultant from this analysis is the evidence of similar definitions in literature attributed to those of 'heating gap' and 'reference heating gap'. The analysis of the literature leads to the conclusion that there is no proof of evidence that the concept of 'heating gap', with its associated 'relaxed comfort', has been studied. Furthermore, studies, where actual energy use is lower than theoretical values assuming reference conditions, were found [27,92,99,100]. Some of these studies aimed to estimate the 'performance gap' and others showed preoccupations in relation to the future energy savings, which resembles the concept behind the 'reference heating gap' (but at an individual level).

Moreover, the study of 'heating gap' and 'reference heating gap' have never been assessed for an entire residential building stock of a city, region or country. It seems, therefore, there is a lot of ground for exploring this issue.

2.2 Characterization of indoor temperatures and heating patterns

2.2.1 Importance of indoor temperatures and heating patterns characterization

Recent medical research has associated low indoor temperatures to various illnesses (e.g. pneumonia, increased blood pressure, asthma, bronchitis, influenza arthritis and heart diseases) and social pathologies (e.g. depression, anxiety, constraints of mobility and isolation) [16,31,32,101–104]. Low indoor temperatures, which are frequently associated with the ´fuel poverty´ phenomena [13,31,101–103], have also a serious impact on mortality [14,16,105]. According to [106], there are approximately 30.000–60.000 excess winter deaths in UK, and 1500–2000 in Ireland related to low indoor temperatures in dwellings. Several international standards define threshold indoor temperatures for health reasons. The proposed indoor temperatures are in the range of 18 to 21ºC, varying as a function of many parameters regulating thermal comfort. For instance, the World Health Organization (WHO) recommends 21ºC in the living rooms and 18ºC in the other occupied rooms to achieve an adequate standard of warmth [107]. Also, the UK Department of Environment proposes as minimum temperatures for health reasons 16ºC in bedrooms and 18ºC in living rooms [108].

Empirical data for residential indoor temperatures and heating patterns have important implications for policymakers in the development of programmes to improve indoor thermal comfort and health conditions. It also has an important role to support energy demand models for the building stock [109] (e.g. more accurate estimations of the actual heating energy use) and energy planning (e.g. studies on the impact of energy efficiency programmes on future energy savings).

The provision of accurate information on indoor temperature and heating patterns (i.e., on occupant behaviour [110]) has become increasingly important over the last decade as governments worldwide move to adopt policies aimed at reducing carbon emissions through improvements to the building stock [24]. Despite the availability of many energy models to support energy planning and policy development it is not often clear which assumptions for indoor temperature and heating patterns estimations are being made and their empirical basis. In most cases operating conditions (i.e., occupant behaviour) are considered standard/reference rather than actual measured conditions [24,53,54]. For instance, the British Research Establishment’s Domestic Energy Model (BREDEM) assumes that living room is heated to 21ºC and other premises to 18ºC for 9h on weekdays and for 16h on weekends [24,111]. However, some authors found out that homes displayed on average lower indoor temperatures during assumed heating periods, and significantly shorter durations of heating than models usually assume. For example, Huebner *et al.* [46] concluded that currently used reference assumptions of heating demand and heating duration do not accurately reflect the living room temperatures in England. Also, Kane *et al.* [20] studied the heating patterns in 249 dwellings in Leicester in UK and concluded that indoor temperatures were much lower than those often assumed by BREDEM-based energy models. This can poses some limitations in a scenario where actual heating energy use values needs to be estimated.

2.2.2 Indoor temperatures and heating patterns

Most of the existing studies in the literature analyze indoor temperatures in UK [8,10,12–14,17,19,31,32,44,50,84,112], southern [33,43,51],southeast European countries [16,24], and non-European countries [37,47–49,52,113–115]. Typically, studies revealed a broad range of indoor temperatures.

For example, Yohanis and Mondol [10] measured the indoor temperatures of 25 households in Northern Ireland at four locations (bedrooms, living rooms, halls, and kitchens) and analyzed data on seasonal, monthly and daily bases. The households were selected from 800 Northern Ireland households based on house type, heating system, number of occupants, location and employment status. In 80% of homes, the winter mean daily temperature was between 15ºC and 20ºC, and in summer between 20ºC and 23ºC, maintaining a reasonably comfortable temperature throughout the year. In 14% of homes, the daily mean temperature was above 21ºC throughout the year, suggesting a higher household temperature than required for comfort, which indicates wasteful energy behaviour. In three percent of homes, the heating was not used adequately and the winter mean temperature was below 15ºC.

More recently, Kane *et al.* [20] verified that mean winter temperatures, measured in the individual homes, ranged from 9.7ºC to 25.7ºC in living rooms, and 7.6ºC to 24.2ºC in bedrooms.

Some studies report low indoor temperatures [9,11,13,14,16,18]. For example, Hunt and Gidman [9] during February and March 1978 undertook spot measurements of the wet- and dry-bulb temperatures in each room of 1000 homes in UK. The mean of the living-room temperatures recorded was 18.3°C, and the mean temperature of the warmest bedroom was 15.2°C. The average dwelling temperature was 15.8°C.

Hutchinson *et al.* [19] analyzed data from five urban areas of England. Half-hourly living-room temperatures were recorded for two to four weeks in dwellings over the winter periods (i.e, November to April in 2001–02 and 2002–03). Overall, 21.0% of the dwellings had daytime living-room temperatures lower than 16ºC, and 46.4% had nighttime bedroom-temperatures below the same temperature. Also, Critchley *et al.* [14] analyzed data from a national survey of 888 dwellings in England occupied by low-income residents over the winters of 2001–02 and

2002–03. A total of 222 households were identified as occupying cold homes, with mean bedroom temperature below 16ºC or mean living room temperatures below 18ºC.

French *et al.* [18] undertook indoor temperature monitoring in over 400 dwellings in New Zealand. Temperatures were logged every 10 minutes during one year in bedrooms and living rooms. The mean living room temperature was 17.9ºC. The maximum mean was 23.8ºC, and the minimum mean temperature was 10ºC. The bedrooms on average always seem to be slightly lower than the living rooms (at the most there is a difference of 3.8ºC which occurs during the evening). This is mainly caused by heating occurring in the living room and, typically, very little or no heating in the bedrooms.

Santamouris *et al.* [16] collected indoor temperature and energy data during the winter 2012–13 from 50 low and very low income dwellings in Athens area in Greece. The results show that indoor temperatures were much below the accepted standards and, in many cases, place in risk the health and even the life of the residents. Table 1 presents temperature monitoring studies.

Table 1. Temperature monitoring studies with broad range of indoor temperatures.

Authors	Location of study	Mean temperature (ºC)	
		Living room	Bedroom
Hunt and Gidman (1982) [9] (n= 1000)	UK	18.3	15.2[a]
Oreszczyn *et al.* (2006) [12] (n=1604)	UK	19.1	17.1
Huntchison *et al.* (2006) [19] (n=470)	England	18.2	16.4
Summerfield *et al*. (2007) [8] (n=14)	UK	20.1	19.3
Critchley *et al.* (2007) [14] (n=888)	England	18.0	16.0
French *et al.* (2007) [18] (n=400)	New Zealand	17.8[b]	15[b]
Yohanis and Mondol (2010) [10] (n=25)	UK	19.4	18.4
Santamouris *et al.* (2014) [16] (n=43)	Greece	15.9[c]	
Kane *et al.* (2015) [20] (n=249)	UK	18.5	17.4

[a]Average temperature of the warmest bedroom;
[b]For the evening period (17:00 to 23:00);
[c]Average between living room and bedroom temperatures.

Heating patterns in the residential sector were also explored by several authors. Kane [116] developed a monitoring campaign in 300 homes in Leicester in UK, and found the following main heating patterns: a) the heating threshold temperature was found to be 8°C to 18°C. This range indicated that some dwellings may be heated throughout the whole year, while others only during the coldest winter months; b) the average duration of daily heating period was 12.6 hours. The longest and shortest heating periods found were 22 hours and 4 hours, respectively; c) the average number of under-heated days was 2.9 in 90 days analyzed; d) two heating patterns dominated the sample; heating was tuned on only once (33%) or twice (51%) per day; e) the most common heating periods were identified (19/20:00 to 23:00) for single heating pattern and (6:00 to 9:00 and 16:00 to 21:00) for double pattern; f) the average temperature during single heating periods was 18.2°C in living rooms and 17.6°C in bedrooms. Dwellings presenting double heating periods achieved an average temperature of 17.5°C in living rooms and 17.0°C in bedrooms in the first heating period, and 19.0°C and 17.8°C in the second heating period, respectively; and g) the average living room temperature was found to be 1.0°C warmer than the average bedroom temperature.

Also, Santamouris *et al.* [16] verified that the absolute energy use for heating purposes in all groups analyzed is quite low. It varied between 4 and 30 kWh/m^2, with an average close to 18 kWh/m^2. The time of use of the heating systems varied between 0.75 and 3h per day, while heating is necessary for much longer depending on the occupancy of the dwellings.

In addition, Audenaert *et al.* [54] characterized the behaviour regarding energy use of 5 Belgium dwellings through surveys. The authors concluded that all heated their living rooms; 4 of them heated their bathrooms; and 3 heated their bedrooms. It was also roughly estimated that 2 heated more than 75% of the floor area, 1 heated 100%, 1 heated between 50% and 75%, and the other heated between 25 and 50% of the floor area.

French *et al.* [18] reported that only 5% of New Zealand houses have central heating, with most houses only heating one or two rooms. Occupants tended to turn a heater on when they arrive, and off when they leave, or when the room is considered to be warm enough. As a result, temperatures that would be considered comfortable elsewhere in the temperate world were often not achieved. The most commonly heated room was the living room which was heated in the evenings in 90% of houses during weekdays, and in 87% of houses during the weekends. Only in 6% of houses did not heat the living rooms. Conversely in 50% of houses the bedroom was never heated, and 68% of houses did not heat utility areas (laundry, bathroom, corridor, etc.). Also, the average length of the heating season ranged from 8.6 months in the cooler far south and 5.5 in the warmer north. Approximately, 4% of the sample heated the entire year. Conversely, 3% of the houses did not heat at all, but these tend to be in the warmer locations. The mean living room, and bedrooms temperature were the highest during the evening (17:00 to 23:00). The mean living room temperature droped from the evening to the night, again not surprisingly as only 18% of houses heated the living room at night (23:00 to 7:00). Only 15% of houses heated the bedroom during the night, but when coupled with the small heat gains from the occupants and appliances, the bedroom temperatures were closer to the living room temperatures overnight and during the morning.

Finally, Burholt and Windle [11] examined a representative sample (N = 421) of older people (aged 70+) living in rural North Wales and concluded that, although only 1% of the respondents did not heat their living room, nearly 18% did not heat a second reception (dining) room. In addition, 16% of respondents did not use any heating in their bedroom. Over one-quarter of respondents did not heat a second bedroom, which may be due to infrequent use of the room. Nearly one-third (31%) of respondents did not heat the kitchen, however, it may be assumed that cooking appliances might increase the heat of the kitchen. Moreover, over one-third (34%) of respondents did not heat the bathroom.

From the literature review, authors that characterized homes as 'cold' regardless of their geographical location were found, which makes empirical investigation of winter indoor temperatures and heating practices imperative. Even in cases where the mean indoor temperatures are high, there is a significant variation between dwellings.

2.2.3 Drivers of indoor temperatures

Several studies scrutinize the driving forces behind indoor temperatures [10,14,16,19,68,115] during winter/heating seasons. The studies analyzed a variety of factors (e.g. climatic conditions, building characteristics and socio-economic factors), that may explain indoor temperatures [70]. For example, Critchely *et al.* [14], using binary logistic regression to model dwelling and household features, concluded that cold homes predominate in pre-1930 properties where the householder remains dissatisfied with the heating system.

Oreszczyn *et al.* [12] monitored indoor temperatures for a period of two to four weeks in over 1600 low income dwellings, and assessed the determinants of indoor temperatures through tabulation and regression methods. The authors concluded that temperatures were influenced by building characteristics (e.g., the age of construction, and the thermal performance of the building) and household features (e.g., the number of occupants, and the age of household´s representant).

Also, Hutchinson *et al.* [19] investigated the extent to which low indoor temperatures in homes can be due to dwelling and household characteristics using tabulation and logistic regression methods. Data of low-income homes, from five urban areas in England, was analyzed. The authors concluded that property and household characteristics provide only limited justification for low winter indoor temperatures, presumably because of the influence of other factors including personal choice and behaviour.

French *et al.* [18] verified that heating type, climate and house age are the key drivers for the living room temperatures. On average, houses heated by solid fuel are the warmest, and houses heated by portable liquefied petroleum gas and electric heaters are the coldest. Over the winter period, living rooms are below 20ºC for 83% of the time, and living rooms are typically the warmest areas.

The relationship between aspects of building quality and indoor temperature has been previously quantified in the study of Haas *et al.*[117]. Authors registered higher indoor temperatures in more insulated dwellings. Another important factor was whether the heating system was centrally controlled and the surface area of the dwelling [70].

Mateo *et al.* [118] applied different machine learning techniques along with other classical ones for predicting the temperatures in different rooms.

In addition, Kelly *et al.* [68] predicted indoor temperatures in English homes using panel methods. The model predicted average daily temperatures using both technical and social household variables, explaining about 45% of the variation in indoor temperatures. In particular, the number of occupants, household income and occupant age were found to be the most important drivers of indoor temperature.

Finally, Santamouris *et al.* [16] found strong correlations between the minimum indoor temperatures and the level of thermal losses of the dwellings, and also between the income levels and the environmental and energy parameters, using regression analysis.

In summary, there is evidence in the literature that some inferences may be drawn when trying to identify drivers for the indoor temperatures. These, or the relevance of each, tend to vary with the geographical area and none was yet found for Portugal.

2.3 Modeling heating energy use

The attention of researchers and experts in building energy performance has traditionally been focused upon a single building rather than on large building stock. This is shown by the increasing number of building thermal behaviour simulation tools on one side, and the increasing interest on certification procedures on the other side [119]. However, when the aim is the evaluation of the global achievable energy savings and Greenhouse Gases reduced emissions, it is also important to widen the focus to the building stock at a regional or national scale [119].

Several methods have been proposed to evaluate the specific energy use of a large building stock as well as of an individual building [120–124]. Commonly they are classified as top-down and bottom-up approaches.

Top-down modeling approach starts with aggregate data and then disaggregate these down as far as possible in a bid to provide a comprehensive model [122]. Some examples include the studies developed by Dineen and Gallachóir [67] and Fabbri [59].

This thesis focused on bottom-up models. Typically these models comprise building physics modeling for calculating the energy usage of individual buildings and extrapolation of the results to a region or a country. The bottom-up approaches are mainly divided into statistical and engineering models [120].

The engineering models use physical principles to predict a building dynamic thermal performance [123]. This can be done in two different methods: a) by using simplified heat-balance equations [60,75,119,125–130]; and b) by using simulation tools [128,131–149].

Simplified heat-balance equations, such those used in the energy rating/energy certification schemes [7] are mostly used tools for individual buildings.

Regarding the building stock, some of the examples that applied the simplified heat balance equations method are presented next. Tommerup and Svendsen [150] gave a short account of the technical energy-saving possibilities that are in existing dwellings in the Danish residential building stock. Detailed calculations have been performed on two typical buildings representing the residential building stock, and then an assessment of the total energy-saving potential is performed on the basis of the calculation. Also, the Building Research Establishment's Housing Model for Energy Studies (BREHOMES) developed in the early 1990s by Shorrock and Dunster [151] used 1000 dwelling types (defined by age group, built form, tenure type and ownership of central heating) as the sample upon which the annual household energy use of UK housing stock is based.

In addition, 8787 dwellings (defined by type, space heating fuels, vintage and province) were used by Farahbakhsh *et al.* [152] to provide the Canadian residential energy end-use model (CREEM) to test the effect of different strategies of carbon reductions based on two standards. The model developed by Larsen and Nesbakken [153] used 2013 dwellings to produce the model of household energy use of the Norway's housing stock. Also, Dineen and Gallachóir [67] developed a bottom-up model of space and water heating energy demand for new dwellings in the Irish residential sector. The basis of the bottom-up archetype approach is to calculate the energy use of a set of archetype dwellings using the engineering method (i.e., based on technical factors such as floor area or area of glazing) and then extrapolate this to the residential sector as a whole.

Dall'O' *et al.* [154] developed a method for monitoring a building's energy performance by integrating the information on the building stock (e.g., cartographic documentation, thematic map, geometric data, etc.) and energy audits (e.g., winter heating, solar photovoltaic (PV) system) based on the GIS platform in Basel. Also, Tuominen *et al.* [155] presented a novel calculation tool for assessing the effects of various energy efficiency measures in buildings on the scale of the whole building stock of Finland. The model developed is a bottom-up model that uses representative building archetypes for estimating energy use in different segments of the building stock.

In addition, Mata *et al*. [146] presented the Energy, Carbon and Cost Assessment for Building Stocks model. This model assesses energy-savings measures and CO_2 mitigation strategies in building stocks. The model is based on a one-zone hourly heat balance that calculates the net energy demand for a number of buildings representative of the building stock.

Finally, Fabbri [59] performed a bottom-up approach by using the single sampling statistic based on the energy performance certificates (EPC) from national databases of Emilia-Romagna Region (i.e., EPBD-derived EPC databases), where each EPC is related to a single urban unit.

Building energy simulation tools are also widely used for prediction of energy use at individual and building stock level. They allow the detailed calculation of the energy required to achieve specific building performance criteria (e.g., space temperature and humidity), under the influence of external inputs such as weather, occupancy and infiltration. Detailed heat-balance calculations are carried out at discrete time-steps based on the physical properties of the building and mechanical systems, as well as on the dynamic external conditions (e.g. weather, occupancy, lighting, equipment loads). These calculations are generally performed over a full year. Some of the main tools used in building simulations are: EnergyPlus, TRNSYS, eQUEST, and ESP-r [123,156]. Although building simulation tools and simplified heat balance equations are currently widely used to predict and analyze building energy use, they are very time-consuming [157,158].

The statistical models have increasingly gained recognition as a viable alternative to predict thermal performance in buildings. The preference for a statistical model relies on the fact that it is possible to predict outputs without resorting to the simulation building software. Thus, these techniques allow to reduce significantly the computation time [159]. Many studies in the literature have explored the ability of different statistical models to predict various variables in the context of energy performance in buildings (EPB) [158]. The statistical methodologies use historical [70,158,160–184], simulated or calculated energy use data to predict a building's energy dynamic performance. There are different statistical models used in the literature, such as the traditional statistical approaches (e.g., the regression analysis) or the artificial intelligence (AI) models (e.g., the neural networks, the support vectors machine, the genetic algorithm, or the decision trees) [123,185].

Table 2 presents some studies that use statistical models to predict building's dynamic thermal performance.

Table 2. Examples of application of statistical models to predict building's dynamic thermal performance.

Authors	Method	Application level
Geem and Roper (2009) [186]	ANN	Building stock
Tian and Choudhary (2012) [149]	Probabilistic approach	Building stock
Howard *et al*. (2012) [187]	Regression analysis	Building stock
Kabak *et al.* (2014) [188]	Fuzzy analytic network	Building stock
Kialashaki and Reisel (2014) [189]	Artificial neural network (ANN) and regression analysis	Building stock
Melo *et al*. (2014) [190]	ANN	Building stock
Buratti *et al.* (2014) [191]	ANN	Building stock
Seo *et al.* (2015) [192]	Nine-node-based Lagrangian finite-element model	Building stock
Lam *et al*. (1997) [193]	Linear and nonlinear regression analysis	Building
Catalina *et al*. (2008) [69]	Nonlinear regression analysis	Building
Jaffal *el al.* (2009) [194]	Regression analysis	Building
Magnier and Haghighat (2010) [195]	ANN	Building
Xu *et al.* (2012) [71]	ANN	Building
Lee *et al*. (2013) [196]	Regression analysis	Building
Ascione *et al.* (2013) [197]	Genetic algorithm (GA)	Building
Asadi *et al.* (2014)[198]	GA and ANN	Building
Paudel *et al.* (2014) [199]	ANN	Building
Rodger (2014) [169]	ANN	Building
Majcen *et al.* (2015) [70]	Regression analysis	Building & Building stock
Capozzoli (2015) [200]	Regression analysis and regression tree	Building

Examples of statistical models applied to residential building stock level are explained next. Tian and Choudhary [149] proposed a probabilistic bottom-up approach to analyze energy saving measure for various non-domestic building sectors. Howard *et al*. [187] developed a model for estimating the building energy use intensity using GIS and robust multivariate linear regression in New York City. Using the developed model, various maps of the annual energy use (e.g., space cooling, water heating, base electric, space heating, etc.) were proposed. In addition, Kabak *et al.* [188] applied a fuzzy analytic network process to the National Building Energy Performance Calculation Methodology in Turkey for categorizing the dynamic energy performance of residential buildings in a simpler way.

Also, Kialashaki and Reisel [189] developed two types of numerical energy models which are able to predict the United states' future industrial energy demand. One model used an artificial neural network (ANN), and the other model used a multivariate linear regression. For building shell energy labelling, Melo *et al*. [190] applied ANNs to model the building stock of the city of Florianópolis (Brazil), based on the results provided by EnergyPlus on a sample of 3200 heterogeneous buildings.

An artificial neural network was also developed by Buratti *et al.* [191] based on approximately 6500 energy certifications received by the Umbria Region in order to evaluate the *global energy performance value* of buildings. This was done using the geometry of buildings, the climate zone and the heating and hot water systems parameters reported in certificates. The *global energy performance value* reported in the certificates was used as a target in the ANN network. Finally, Geem and Roper [186] proposed an ANN model to estimate the energy demand of industrial sector for South Korea. The data was obtained from diverse local and international sources.

The statistical models are also widely applied to individual buildings. Some examples of the studies that use regression analyses are explained next. Lam *et al*. [193] used the nodal software DOE-2 as a database generator and applied multivariate linear and nonlinear regression models. The authors were able to identify the annual energy use function of 12 selected variables in air-conditioned office building in Hong-Kong. Similarly, Lee *et al*. [196] proposed to couple a regression analysis with a thermal simulation model to describe the influence of the size, thermal properties and orientation of windows in buildings considering 5 different climate zones in Asia.

Catalina *et al.* [69] tested various models between the heating demand of single-family residences and four predictor variables: shape factor, envelope U-value, window to floor area ratio, building time constant, and climate coefficient. The data used was obtained with hourly time-step simulations performed using the building simulation software TRNSYS. The best model was found to be a polynomial, which predicted the data used with an error ranging between 1.2–5.2%. Also, Jaffal *et al.* [194] developed a regression model to estimate the influence of the building envelope parameters on the annual energy demand. The data on parameters was obtained from dynamic simulations.

Recently, Majcen *et al.* [70] performed regression analysis to predict actual gas use (from statistics office´s data) and theoretical gas use (from EPBD-derived database) for Dutch buildings (at individual and building stock levels). It also developed a model for determining actual gas use from theoretical gas use data and dwelling characteristics.

Some examples of studies that use artificial neural networks (ANN) are also applied at individual building level. Xu *et al.* [71] established a model coupling the nodal software EnergyPlus with an ANN for predicting energy use. More specifically, they generated a database from the thermal model and use them as input parameters in the ANN. Magnier and Haghighat [195] used TRNSYS simulations and an ANN for the optimization of thermal comfort and energy use in a residential house. The database for training the ANN consisted on data from 450 simulations.

In addition, Asadi *et al.* [198] presented a multi-objective optimization model using genetic algorithm (GA) and ANN to assess technology choices in a building retrofit project. The study presented a set of mathematical models to estimate the electric lighting energy demand for rooms with different architectural features, lighting system characteristics or users' lighting requirements. The models were built upon the data obtained from simulations carried out using 828 case-studies through Daysim. Rodger [169] predicted demand for natural gas to infer on energy cost savings. The system was modeled with ANN. More recently, Paudel *et al.* [199] presented a building heating energy demand model with occupancy profile and operational heating power level characteristics in short time horizon using ANN.

Other statistical models are also used in scientific work. Some examples are: Capozzoli [200] analyzed the heating energy use of eighty schools buildings located in the North of Italy. Two estimation models were developed and compared to assess energy use: a multivariate linear regression and a classification and regression tree. Also, Ascione *et al.* [197] performed a genetic algorithm implemented using EnergyPlus and MATLAB softwares to identify the cost-optimal package of energy efficiency measures.

From the literature review it is possible to observe that there are several proven top-down and bottom-up methods to estimate heating energy use at a building stock and individual level. The literature review also revealed that there are no models developed so far that predict heating energy use, for different levels of occupant behavior, from the theoretical heating energy demand under reference conditions (HDRC) values, which can be easily extracted from EPC databases. The closest evidence is the model of actual gas use (from theoretical gas use values from EPBD´s derived database) developed by Majcen *et al.* [70]. However, it is only applicable to Dutch residential buildings and it only models actual gas use.

CHAPTER 3

CHARACTERIZATION OF THE STOCK AND THE ASSESSMENT OF THE 'REFERENCE HEATING GAP'

Given the sparse data on the building stock, the existence of databases, such as EPBD-derived EPC databases, with the thermal performance characterization of a large number of buildings, construction periods and building typologies, enables gaining new insights relevant for several dimensions of policy assessment and policy design.

This chapter explores the use of these databases to assess two main issues: 1) How does the thermal performance of the existing residential buildings stock vary with the year of construction in Portugal mainland?; 2) What is the difference between the 'theoretical heating energy demand under stringent comfort conditions' (THD_{stcc}) (*(1)* in Figure 1, section 1.2) and the 'actual energy use' (*(3)* in Figure 1, section 1.2) for heating, i.e., the 'reference heating gap' for the existing residential building stock in Portugal mainland?

From an energy management of a country or region point of view, these objectives provide a new perspective on the characterization of the thermal performance of the existing residential building stock versus the current individual analysis of the buildings. They will also give an indication of the relevant importance of the nature evolution of thermal performance vs the evolution triggered by regulations. The assessment of the existence and quantification of energy use gaps is also relevant for energy planning and policy making as they establish implications in the future energy demand and energy savings (see section 1.2).

The remainder of this chapter is structured as follows. Section 3.1 contextualizes the EPBD in Portugal and section 3.2 presents the characterization of the Portugal mainland residential building stock in terms of construction period. Section 3.3 characterizes the thermal performance of the residential building stock, whereas section 3.4 addresses the methodology behind the estimation of the theoretical energy demand for the existing residential building stock. Section 3.5 presents the estimation of the gap between theoretical energy demand and actual energy use for space and water heating. Finally, section 3.6 presents the main conclusions of the study developed under this chapter.

3.1 The Energy Performance Building Directive in Portugal

The thermal performance of buildings, both in terms of energy demand and actual energy use, has attracted the attention of several social, industry and policy stakeholders. Most developed countries adopted regulations concerning this issue in the 20th century [201,202]. In Portugal, this was done through the regulation of the characteristics of thermal behaviour of buildings (RCCTE), Decree-law nº 40/90 in 1990 [203]. It was the first legal instrument to impose minimum standards on the thermal quality of the building envelope and it intended to achieve an 'improvement of the comfort without additional energy use'. This was followed by the first regulation for energy systems and heating, ventilation and air conditioning (HVAC) systems in buildings (Decree nº 118/98) [204].

In 2000, the European Commission fostered the advance of energy efficiency in the building sector by publishing the thermal performance of building Directive (EPBD) in 2002 (Directive 2002/91/EC) [6]. This Directive proposes the adoption of structured methodologies for calculating the energy use in buildings, quality requirements for new and existing buildings, and the periodic inspection of boilers and air conditioning central systems. In addition, it requires the existence of an energy certificate of all buildings when undergoing a commercial transaction. In this regard, the directive changed the focus from new buildings only to the entirety of the building stock.

All European Union Member States require an energy performance certificate (EPC) when buildings are constructed, sold and rented. The EPC was considered a pioneering instrument that would overcome a deficit of information, hindering consumer interest in energy efficient dwellings [66]. The copies of all the EPC certificates issued both for new as for existing buildings are compiled in databases.

The 2002 Directive was recast on May 2010 as 2010/31/EU Directive [7]. This recast Directive was published and adopted by the European Parliament and the Council of the European Union in order to further boost EU buildings´ energy efficiency following the EPBD.

The 2002 European EPBD was transposed to the Portuguese legislation in 2006 through three Decrees: Decree 78/2006 created and defined the Portuguese thermal performance certification of buildings system (EPC) [205]; Decree 79/2006 updated the regulation for building energy systems and HVAC of buildings (RSECE) [206]; Decree 80/2006 updated the regulation on the characteristics of thermal behaviour of buildings (RCCTE) [72]. The overwhelming majority of residential buildings are covered by the first and the third ones, which will be closely referred in the present work. ADENE (the Portuguese Energy Agency) is the regulatory authority for building energy certification and energy efficiency under the supervision of the General Directorate of Energy and Geology (DGEG), and the Portuguese Agency of Environment (PAA) deals with issues related to the indoor air quality in buildings. The key objective for implementation was to save energy while ensuring comfortable indoor conditions and acceptable indoor air quality [207].

In turn, the recast EPBD (2010/31/EU Directive [7]) was transposed into Portuguese legislation in 2013 through the Law Decree 118/2013 [73].

3.2 Characterization of the Portugal mainland residential building stock in terms of construction period

In order to characterize the Portuguese residential building stock, ADENE's National energy performance certification system (EPC)´s database was accessed in February 2012. The EPC´s database is the Portuguese database derived from the EPBD Directive that holds the energy performance certificates issued, i.e., the Portuguese EPBD-derived EPC database. Since 2009, the ADENE has been compiling statistical data, aiming at characterizing different aspects related to the energy performance of the building stock. These include general aspects, (e.g., the distribution of the ratings of EPCs issued for new and existing buildings) and also detailed technical information (e.g., the average envelope characteristics for new construction in different decades) [208].

At that point of time, the EPC´s database only included certificates issued under the former RCCTE regulation [72]. Each certificate corresponds to an autonomous fraction (i.e., an apartment, detached or semi-detached dwelling). Both certificates for new and existing buildings, with or without heating or cooling systems were considered. Provisional certificates for new buildings still not completed were left out. The analysis covers the whole of the Portugal mainland municipalities, leaving out the buildings from the autonomous regions of Azores and Madeira that have autonomous and different databases. There were 259775 certificates able to be included in the analysis, which represent 5% of the total Portugal mainland residential building stock as of 2011. The National Institute of Statistics (INE), the entity responsible for ensuring the production and dissemination of official statistical information, designates the Portuguese residential building stock as the total of the usual residence, secondary residence and non-occupied autonomous fractions.

It is important to introduce the main theoretical evaluation values of RCCTE used within the EPC. For each autonomous fraction (i.e., an apartment or a detached dwelling) under assessment, it is necessary to compute the theoretical energy demand for heating (HDRC)[3] and cooling (CDRC)[4] under reference conditions (in kWh/m^2.year of 'useful'[5] energy), as well as theoretical energy demand for domestic hot water under reference conditions (DWDRC)[6] (in kWh/m^2.year of 'final' energy). The calculation method is detailed in [72] and it follows the methodology of EN 13790 [209]. These are then integrated into a theoretical value of fossil

[3]Named as 'Nic' in RCCTE regulation [72].
[4]Named as 'Nvc' in RCCTE regulation [72].
[5]'Useful energy' is not what consumer buys (i.e., 'final energy) but rather that from which the consumer derives benefits, after losses in the technical systems installed in the building have been taken into account [146].
[6]Names as 'Nac' in RCCTE regulation [72].

‘primary energy’ demand under reference conditions (PDRC)[7] (in kgoe/m^2.year), as represented in Eq. 3.1 [210]. All of these evaluation values are computed considering reference operating conditions, which consider that buildings are kept at 20ºC during the whole heating season and at 25ºC during the whole cooling season, and also that each occupant uses 40l/day of domestic hot water at 60ºC. These four values must be lower than the reference limit.

$$PDRC = 0.1 \times \frac{HDRC}{\eta_i} \times F_i + 0.1 \times \frac{CDRC}{\eta_v} \times F_v + DWDRC \times F_a < Nt = 0.9 \times (0.01N_i + 0.01N_v + 0.15N_a) \quad [\mathrm{kgoe}/m^2.\mathrm{year}] \quad \textbf{Eq. 3.1}$$

where, η_i and η_v are the conversion efficiency from ‘useful’ to ‘final’ energy for heating energy demand and cooling energy demand, respectively. F_i, F_v and F_a are the conversion efficiency from ‘final’ to ‘primary’ energy for heating energy demand, cooling energy demand, and water heating energy demand, respectively. N_i, N_v, and N_a are the reference limit of ‘useful’ heating energy needs, cooling energy needs and domestic water heating energy needs, respectively.

Regarding the quality of the assessment performed, it has been shown that the values derived through the RCCTE methodology are correlated with those obtained through dynamic building simulation for the same buildings [211]. The main sources of disparities, during the evaluation of existing buildings, arise when some important characteristics are not known neither can be assessed *in situ*. In the absence of better information for a certain required parameter the experts must use the reference values, suggested by the energy certification system [72,210,212,213].

During the energy audit of an autonomous fraction, the performance values and other building characteristics are gathered together to build up a certification, collected afterwards into the EPC database. From each certificate included in the database, it is possible to extract information regarding the floor area (m^2), year of construction, number of bedrooms, heating energy demand (HDRC), cooling energy demand (CDRC) and domestic water heating energy

[7]Named as ‘Ntc’ in RCCTE regulation [72].

demand (DWDRC), all expressed in kWh/m^2.year, and the primary energy demand for heating, cooling and domestic hot water (PDRC), expressed in kgoe/m^2.year.

Other complementary data for Portugal mainland residential building stock were retrieved from the INE [214]. The INE carries out, on a regular basis, the Census, a large statistical survey on the Portuguese population and housing. The most recent one took place in 2011 (Census 2011) [214]. Figure 3 presents the total recorded Portugal mainland residential building stock as of 2011 (from INE´s database [214]) and Figure 4 shows the number of certificates (from EPC database), both per slot of construction period and number of bedrooms. Note that, in the EPC database, data after 2007 regards all buildings finished in a given year, and data before 2006 includes buildings that have undergone a commercial transaction (sale or rental) since 2009. This explains the high quantity of certificates in the last column of Figure 4.

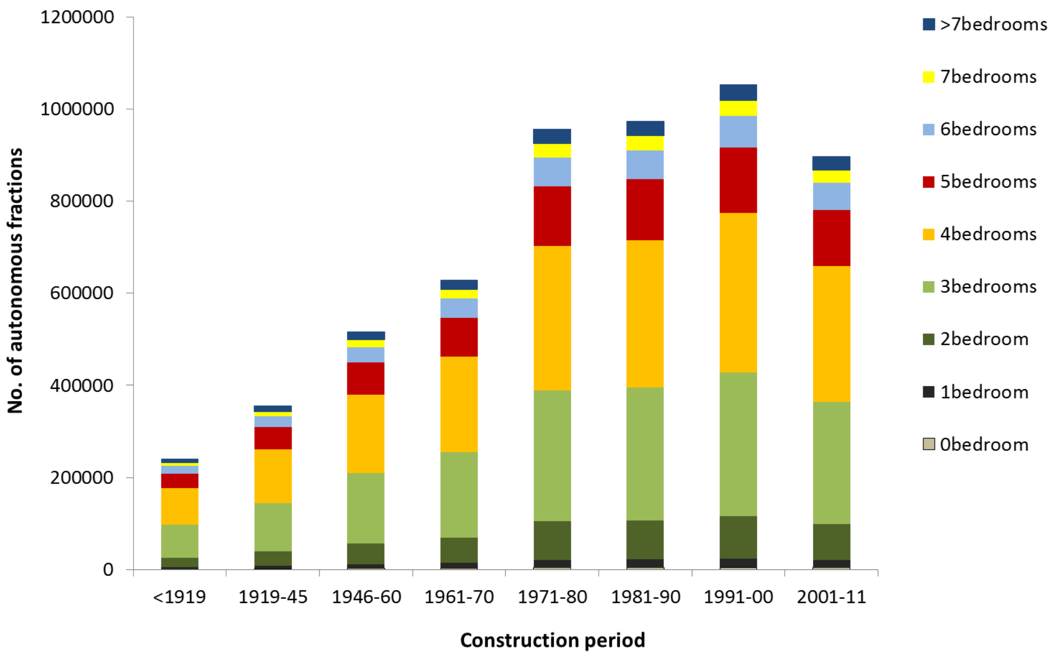

Figure 3. Portugal mainland residential building stock per construction period and number of bedrooms as of 2011 (from INE´s database [214]).

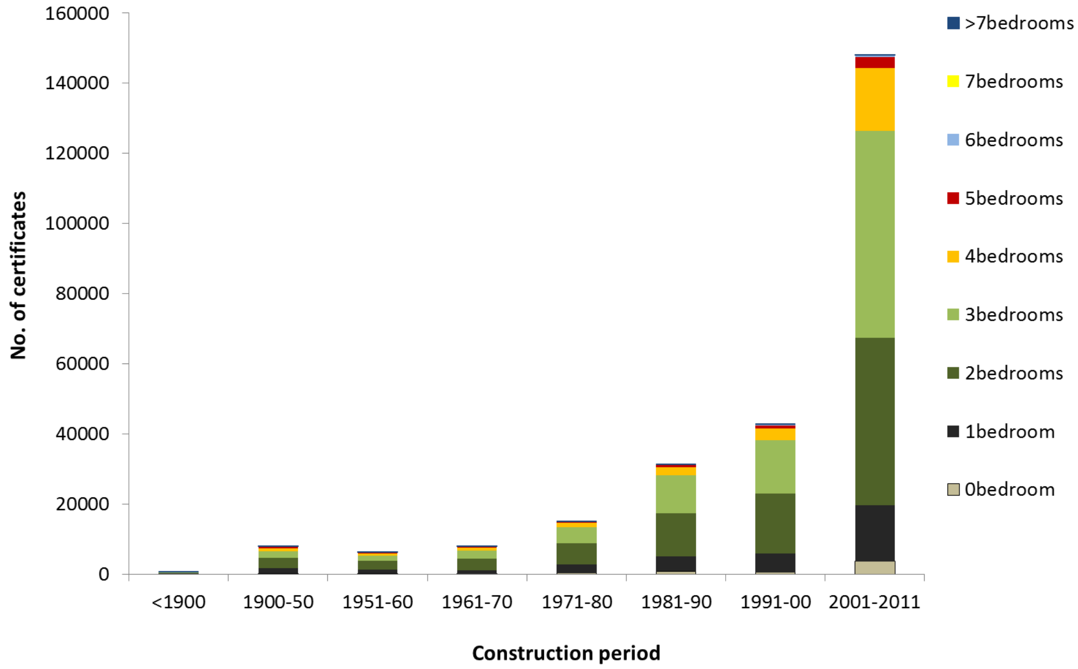

Figure 4. Number of certificates from EPC database per construction period and number of bedrooms.

The Portugal mainland residential building stock was then re-characterized in accordance with the timescale and specific average floor area (per construction period and number of bedrooms) of EPC certificates sample. Figure 5 represents the total built area of the Portugal mainland residential building stock as of 2011 per construction period and number of bedrooms.

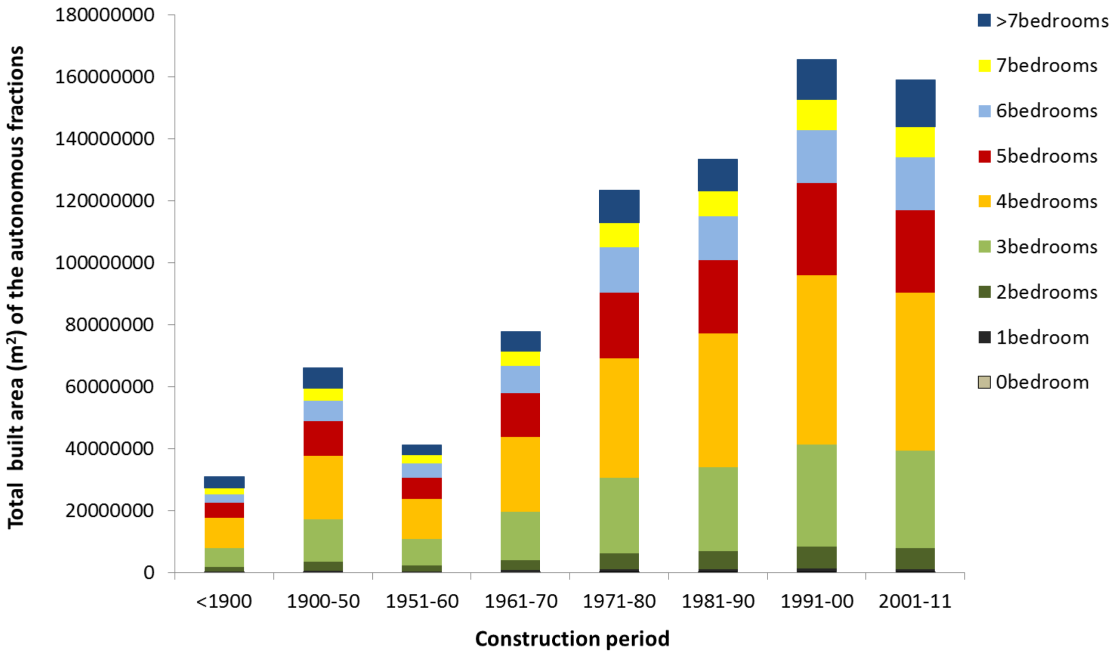

Figure 5. Portugal mainland residential building stock total built area per construction period and number of bedrooms.

The results from Figure 3 make evident that, in terms of number of autonomous fractions, the predominant building slots are those from the decades of 1990 and 1980, followed by the decades of 1970 and 2000. However, analyzing the building stock in terms of total built area (Figure 5), the predominant slots are those from the decades of 1990 and 2000, followed by 1980 and 1970, indicating that apartments and dwellings have become larger.

3.3 Characterization of the thermal performance of the residential building stock

3.3.1 Evolution over time and hypothetical effects of regulations

Currently, the analysis regarding the impact of the energy performance certification system becomes possible in the European Union. As the energy performance certification system was implemented several years ago, it is now possible to examine its impact [66]. Several studies have looked into EPBD implementation in different European countries showing a potential to increase energy efficiency (see, for instance, the study performed by Dascalacki *et al*. [215] in Greece, Amecke [65] in Germany, Tronchin and Fabbri [216] and Salvalai [217] in Italy, Ekins and Lees [218] in UK, Araùjo *et al.* [219] in Portugal, Murphy [66] in Netherlands and Gangolells *et al.* [220] in Spain).

In addition, Casals [221] analyzed the building energy regulation and certification in Europe in terms of their role, limitations and differences. More recently, D´Agostino [222] provided an overview of the European status towards the implementation of nZEBs. Carpio *et al.* [223] determined the strengths and weaknesses of EPBD regulamentation in Europe by comparing opinions of 105 professionals. Fabbri [59] described how the energy performance certificates can be used as a value to measure features of their own building estates.

Furthermore, Dall'O *et al.* [224] provided results of a benchmarking study on data from the energy cadaster of the Lombardy Region in Italy. The study identified key indicators on the energy performance of existing buildings, which became an effective tool for energy planning at local and regional scales.

In order to try to detect the effects of regulations on the thermal performance of the Portugal mainland residential building stock, the average of the theoretical evaluation values (HDRC, DWDRC, CDRC and PDRC), collected from the EPC certificates sample, were plotted according to the year of construction. Only the most represented categories of the number of bedrooms (i.e., 2 to 5 bedrooms) of the residential building stock were considered.

Figure 6 and Figure 7 present the evolution of the average of the theoretical HDRC and CDRC. Figure 8 and Figure 9 present the evolution of the theoretical DWDRC and fossil primary energy (PDRC). The equations used to compute the values represented are shown in Appendix A. The years of 1990 and 2006, dates of introduction of the first and second versions of the RCCTE, are marked to help the interpretation of the graphics.

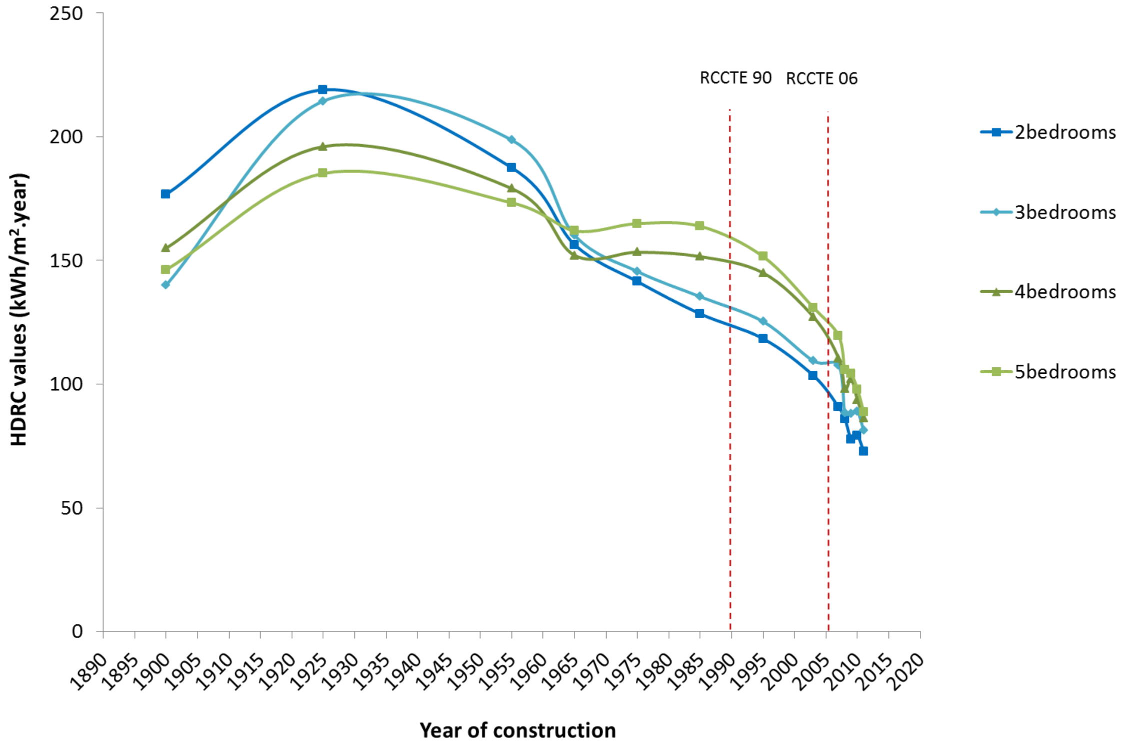

Figure 6. Evolution of the average theoretical heating energy demand under reference conditions (HDRC) with year of construction.

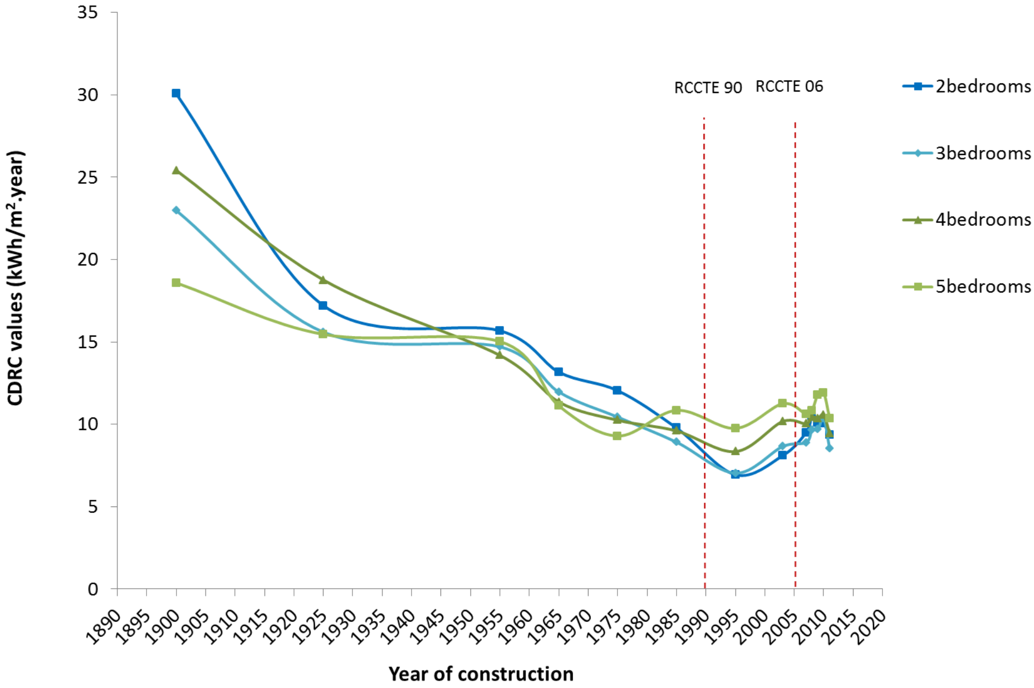

Figure 7. Evolution of the average theoretical cooling energy demand under reference conditions (CDRC) with year of construction.

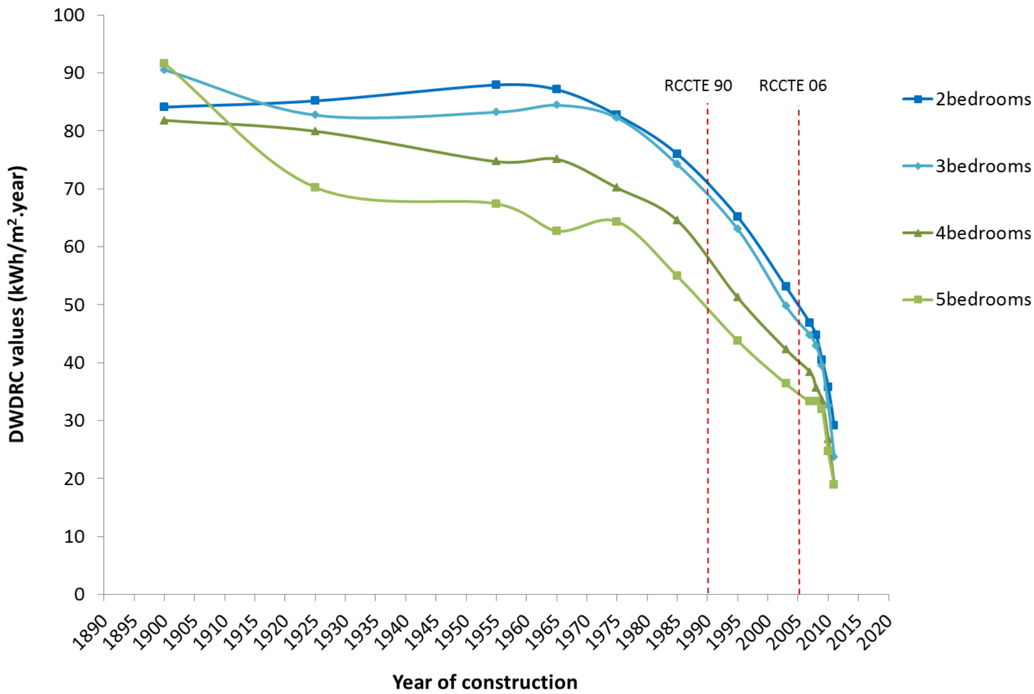

Figure 8. Evolution of the average theoretical domestic hot water energy demand under reference conditions (DWDRC) with year of construction.

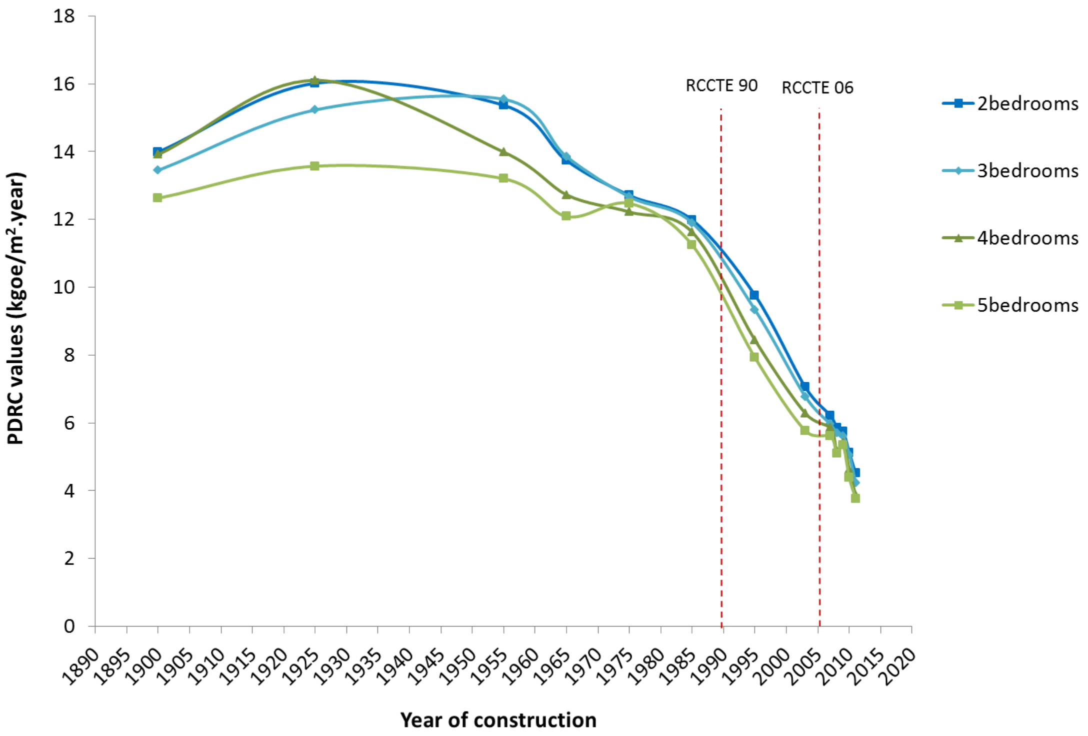

Figure 9. Evolution of the average theoretical fossil primary energy demand under reference conditions (PDRC) with year of construction.

Table 3 summarizes the variations of the HDRC, DWDRC, CDRC and PDRC weighted average values within each construction period analyzed. The values were calculated making use of the data shown in Figure 6 to Figure 9.

Table 3. Variations of HDRC, CDRC, DWDRC and PDRC weighted average values within construction period.

Construction period	ΔHDRC	ΔCDRC	ΔDWDRC	ΔPDRC
1900-50 vs <1900	+29%	-30%	-7%	+13%
1951-60 vs 1900-50	-9%	-11%	-1%	-4%
1961-70 vs 1951-60	-16%	-20%	-1%	-10%
1971-80 vs 1961-70	-4%	-9%	-4%	-5%
1981-90 vs 1971-80	-4%	-10%	-9%	-5%
1991-00 vs 1981-90	-6%	-18%	-17%	-23%
2001-06 vs 1991-00	-13%	+20%	-19%	-26%
2011 vs 2001-06	-30%	0%	-50%	-37%

Results from Table 3 show that, in general, the HDRC and DWDRC weighted average values tend to decrease with the construction period. This confirms that, buildings have been requiring less reference space and water heating energy demand as construction methods improve, more efficient equipment is adopted, and/or, as cleaner energy vectors are introduced, as it is the case of the solar thermal energy for domestic hot water heating.

Overall, the four theoretical evaluation values of RCCTE have become less dependent on the size of the dwelling (expressed by the number of bedrooms) as the values are getting closer to each other for recent construction periods. Another conclusion is that, for DWDRC values, smallest autonomous fractious are penalized by the expression of the performance in terms of kWh/m^2 instead of kWh/person.

Analyzing the heating demand (HDRC values) in Figure 6, the first considerable decrease of the reference values is observed around 1960. This was probably associated with the introduction of the hollow bricks to complement or replace the stone in the buildings walls [225]. Other measures that contributed for a better thermal performance can be associated with the introduction of air layers in the walls, and years later, the thermal insulation. The steep decrease of the heating demand between 1991-06 may be a reflex of a slow adoption of the 1990 regulation by designers and builders combined with a natural market evolution. The significant decrease after 2006 may be a result of the 2006 RCCTE regulation coupled with the Portuguese energy certification system, which had a very powerful enforcement mechanism and ensured a rapid adoption in practice.

The downward trend of the CDRC values plotted in Figure 7 is not as consistent as for the HDRC values, especially after 1990. Overall, the trend shows a decrease until the end of the 20th century, but there is an increase since the beginning of the 21st century. This possibly reveals changes in architecture tendencies and styles, such as the increasing of windows/glazed area and the less use of outdoor shadings. The introduction of new materials and construction techniques, such as the substitution of cement by gypsum-based lightweight materials in the indoor finishing of walls, also reduced the thermal inertia.

Analyzing the pattern of DWDRC in Figure 8, the values declined from 1981-90 onwards. This may reflect the evolution of the efficiency of the technology, with an emphasis on the improvement of gas boilers. The decrease of about 50% between the decade of 2001-06 and the decade of 2011 is almost certainly due to the adoption of solar thermal collectors for domestic hot water, mandatory since 2006 RCCTE.

The PDRC values represent the total primary energy needed and the global pattern of PDRC decreases as buildings construction gets improved just after the decade of 1950 (Figure 9). Significant reductions are seen after the decades of 1980, 1990 and 2006. This behaviour follows the trends of HDRC and DWDRC commented in the previous paragraphs.

In summary, it is found that the evolution of the theoretical evaluation values seems to be the result of natural evolution (likely including '*spill-over*' effects from other countries policies) and national regulations. Regarding the latter, it seems that the adoption of 2006 RCCTE was more effective than 1990 regulation.

3.3.2 Disaggregation of the stock by thermal performance levels

This section presents a disaggregation of the average values by levels of the theoretical evaluation values (HDRC, DWDRC, CDRC and PDRC). Figure 10 and Figure 12 to Figure 14 present the distribution of total built area by levels of HDRC, DWDRC, CDRC and PDRC values, respectively. The equations used to compute the represented values are shown in Appendix A. Figure 11 shows the frequency of exceedance of the total built area (m^2) of the residential building stock per levels of HDRC values.

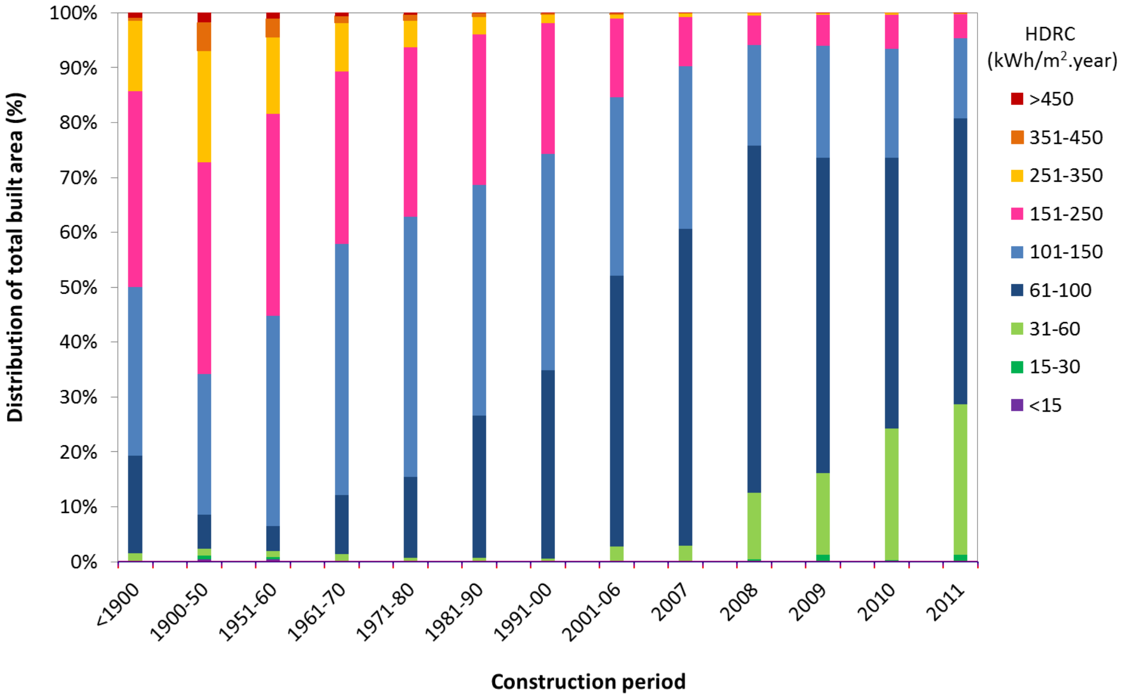

Figure 10. Distribution of total built area by levels of theoretical heating energy demand under reference conditions (HDRC, kWh/m^2.year).

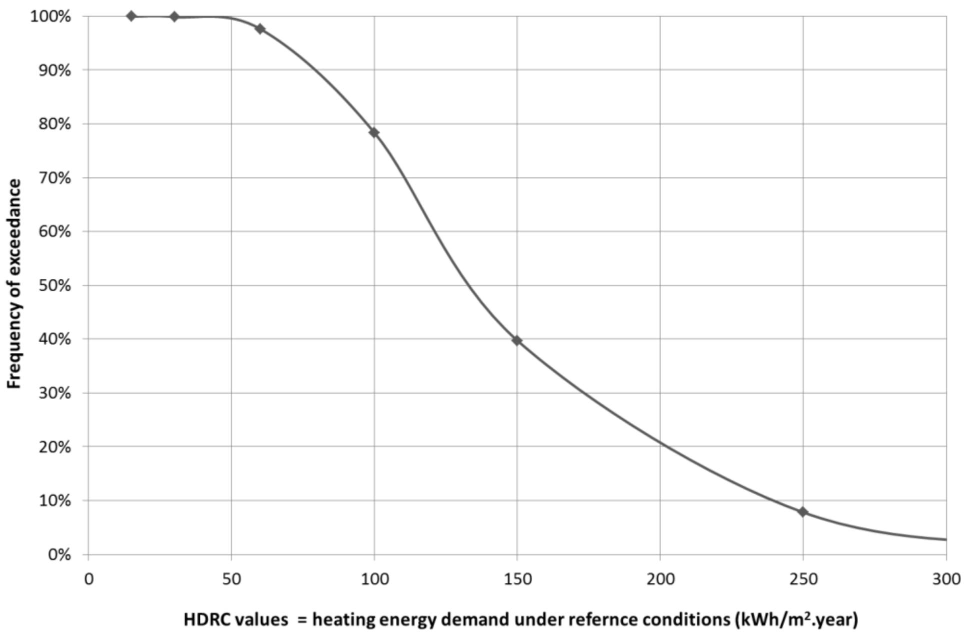

Figure 11. Frequency of exceedance of theoretical heating energy demand under reference conditions (HDRC, kWh/m^2.year) of the Portugal mainland residential building stock in terms of built area.

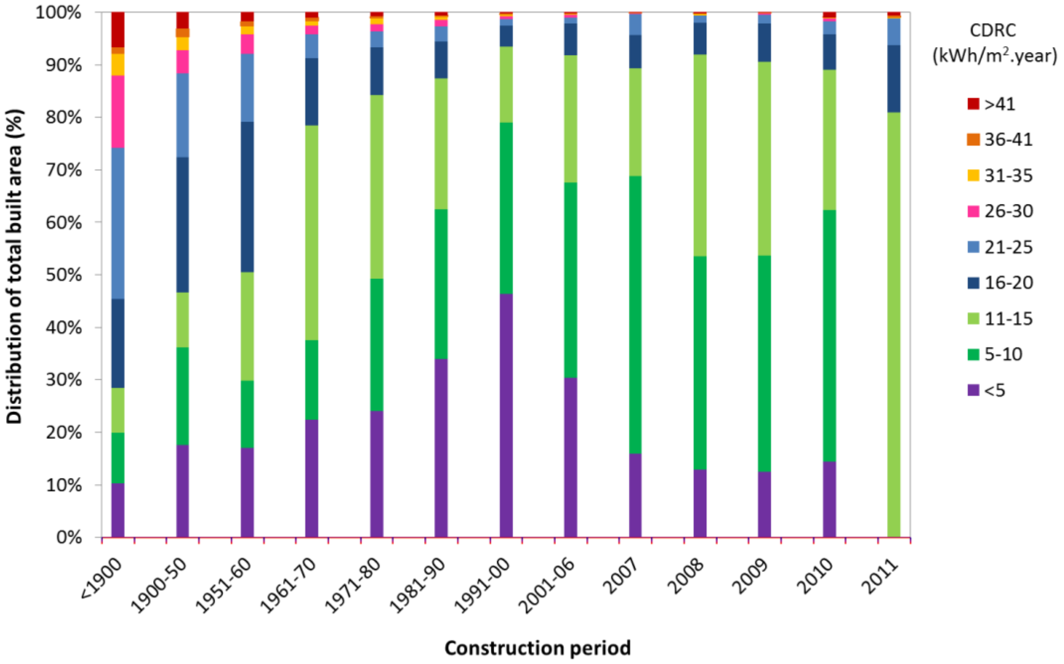

Figure 12. Distribution of total built area by levels of theoretical cooling energy demand under reference conditions (CDRC, kWh/m^2.year).

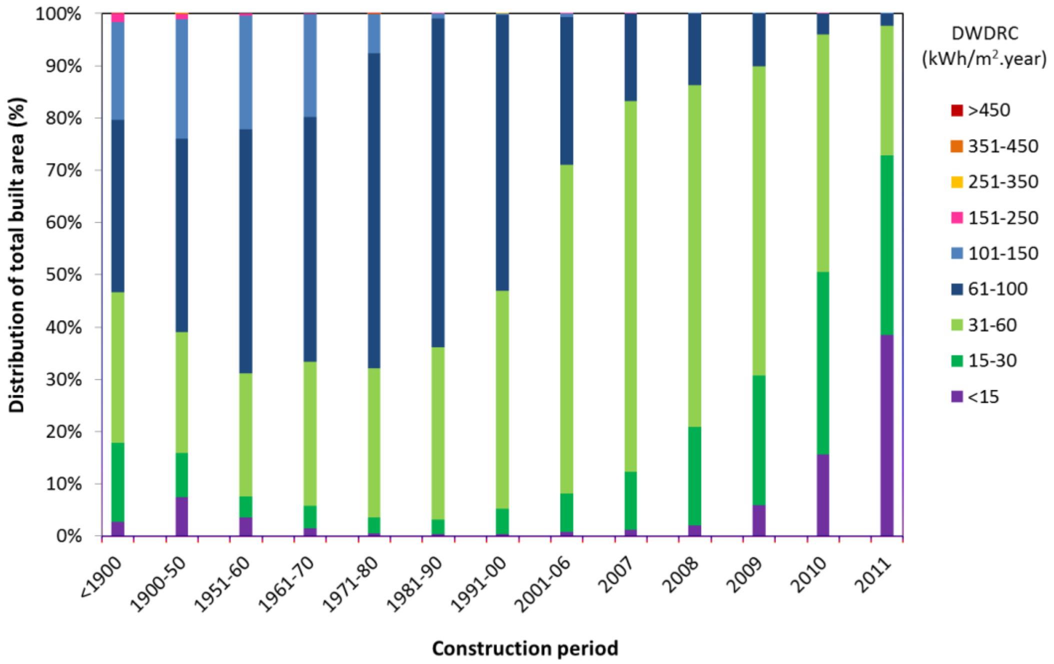

Figure 13. Distribution of total built area by levels of theoretical domestic hot water energy demand under reference conditions (DWDRC, kWh/m^2.year).

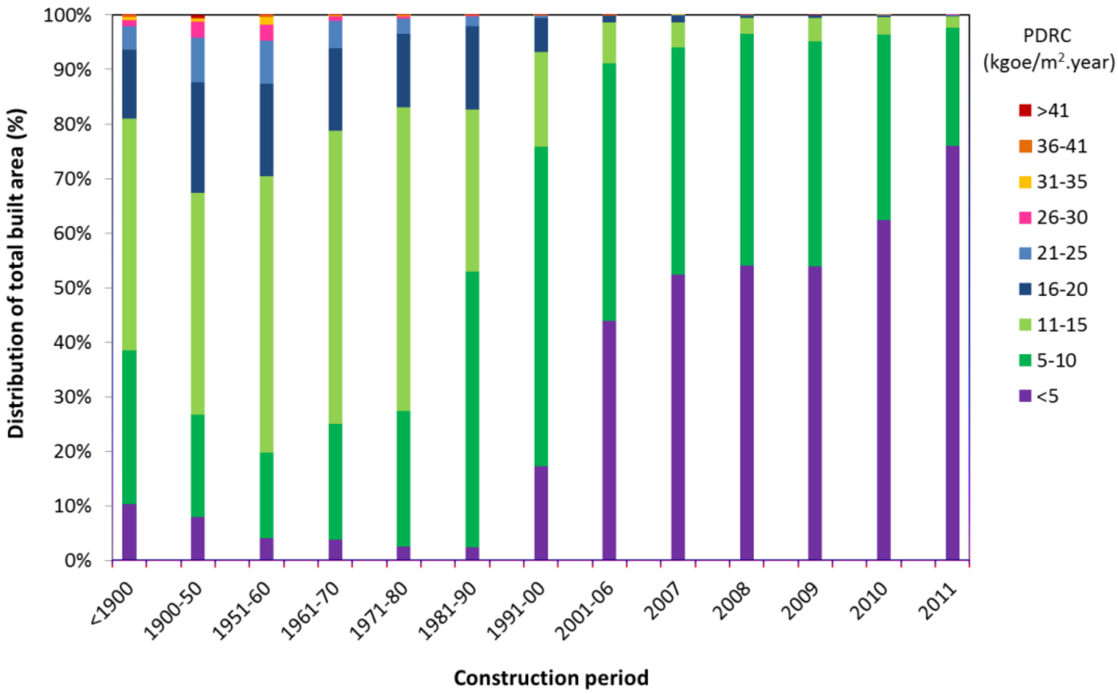

Figure 14. Distribution of total built area by levels of theoretical fossil primary energy demand under reference conditions(PDRC, kgoe/m^2.year).

The results from Figure 10 confirm that the recent buildings present better thermal performance as the biggest share of certificates are within lower levels of HDRC (heating demand in 'useful' energy). Most of the buildings constructed in 2011 have HDRC average values in the range of 61-100 kWh/m^2.year, whereas the second group is in the range of 31-60 kWh/m^2.year. Most buildings completed before 2000 have HDRC values higher than 100 kWh/m^2.year. Figure 11 shows that the fraction of total built area with HDRC values lower than 50 kWh/m^2.year is negligible, about 80% has heating demand higher than 100 kWh/m^2 per year, and about 20% has heating demand higher than 200 kWh/m^2 per year.

Regarding the levels of CDRC (Figure 12, cooling demand in 'useful' energy), it can be observed that, after 1950, most of the certificates have levels of CDRC lower than 15 kWh/m^2.year. The share of certificates with levels lower than 15 kWh/m^2.year increased until 1991-00 and then decreased until 2008, remaining nearly constant since then. This is even more evident when observing certificates with values lower than 5 kWh/m^2.year.

In terms of DWDRC values (Figure 13, demand for DHW in 'final' energy), it is observed an increase in the share of certificates with low reference values from buildings constructed from the 1980's onwards, with some acceleration 2000 onwards.

Finally, regarding the PDRC (Figure 14, primary fossil energy for heating, cooling and DWH), it is clear that the number of buildings with PDRC demand lower than 5 kgoe/m^2.year have been increasing more expressively since the 1990's. Nearly all buildings built after 2001 meet this condition.

Considering the current policy objectives of achieving 'nearly zero energy buildings' adopted in the EBPD recast [7], it is worth mentioning that the absolute values of energy demand are still very high and have to significantly decrease in the near future if policy objectives are to be met (e.g., under the Passivhaus concept the building must be designed to have an annual heating demand of not more than 15 kWh/m² per year in heating, and 15 kWh/m² per year in cooling energy, OR to be designed with a peak heat load of 10 W/m² [226]).

3.4 Theoretical energy demand under reference conditions: A majorant for the country's theoretical energy demand under thermal comfort conditions

Providing an estimate of the theoretical energy demand to meet thermal comfort needs would be of great interest to the modeling and planning of countries' energy systems. In this regard, data gathered in the previous sections of the present chapter is of most interest for this problem, in particular for space heating.

It must be recognized that the theoretical evaluation values of RCCTE, computed under reference conditions (e.g., never less than 20ºC indoors during all winter, and never more than 25ºC during all summer) are most likely too stringent regarding the habits in residential buildings in Portugal and other countries. Nevertheless, at this stage, the theoretical evaluation values will be used to establish a 'majorant' objective (i.e., will be used as direct values) of the theoretical energy demand under thermal comfort conditions for the residential building stock of the Portugal mainland (see section 1.2).

Following this goal, the HDRC, CDRC and DWDRC values found in section 3.3.1 were multiplied by the respective total built area (m^2). The total annual values of theoretical energy demand under reference conditions, resulted from the bottom-up assessment, are presented in Figure 15 (the respective equations in Appendix A).

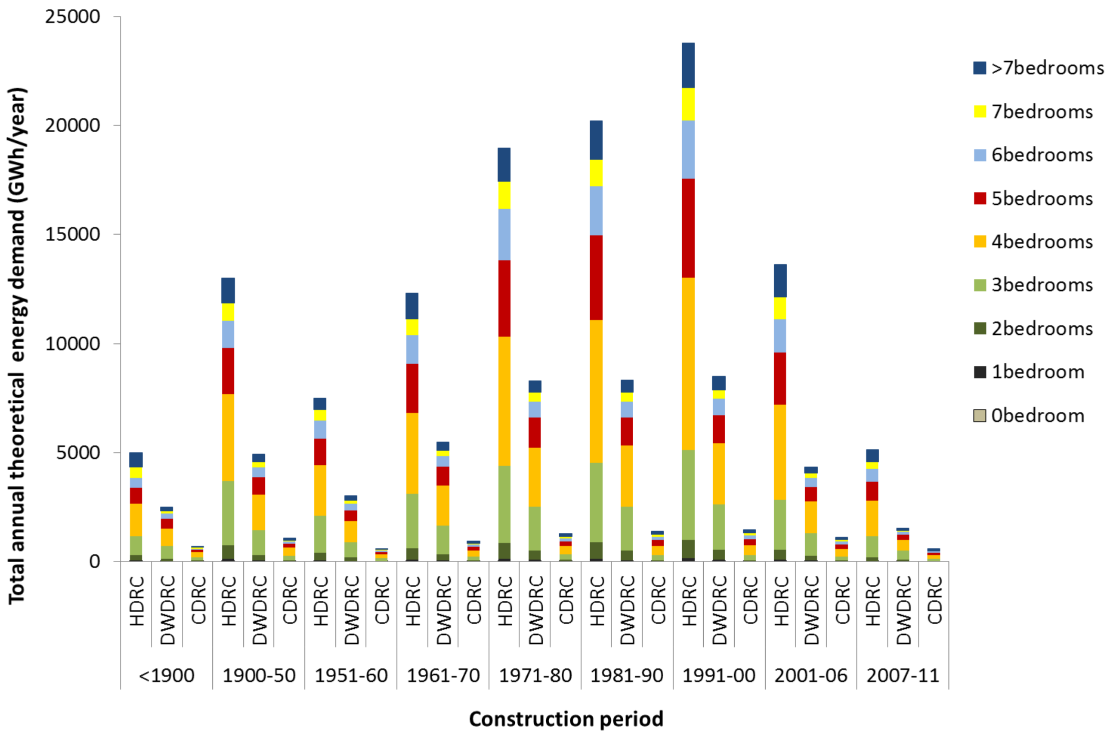

Figure 15. Total annual theoretical energy demand for heating (HDRC), DHW (DWDRC) and cooling (CDRC) under reference conditions (GWh/year), per construction period and number of bedrooms.

The results show that the Portugal mainland residential building stock in 2011 is characterized by a total annual theoretical energy demand under reference conditions of 119469 GWh for space heating, 9129 GWh for space cooling and 46885 GWh for domestic water heating (Figure 15). To be noted that, as detailed in section 3.2, HDRC and CDRC are evaluated at the level of 'useful' energy, DWDRC is evaluated at the level of 'final' (or 'delivered') energy and PDRC is evaluated at the level of fossil primary energy.

The slots that represent a higher energy demand per construction period are those of the decades of 1971-00 (Figure 15). The absolute energy demand values for buildings constructed after 2006 represent only a small portion of the total. Overall, the 4 bedroom´s dwelling is the most representative in the total annual energy demand of the building stock.

As the number of Portugal mainland autonomous fractions, as reported by INE, includes usual residence, secondary residence and non-occupied autonomous fractions, it would be worth disaggregating the annual theoretical energy demand for these three categories. The results of this procedure are presented in Table 4.

Table 4. Annual theoretical energy demand under reference conditions of the Portugal mainland residential building stock as of 2011 disaggregated per usual residence, secondary and non-occupied residences.

Theoretical energy demand under reference conditions	Usual residence	Secondary residence	Non-occupied residence
HDRC (GWh/year)	81044	23380	15045
CDRC (GWh/year)	6094	1775	1260
DWDRC (GWh/year)	31805	9105	5975

It is found that about 1/3 of the total annual theoretical energy demand of the residential building stock is due to secondary and non-occupied residences. It seems advisable to remove those from the figures when trying to compare energy values for heating from bottom-up vs. top-down approaches, as it will be the case of the next section. Also, the bottom-up values for the usual residence energy demand were computed now considering the residential building stock until the year of construction 2010 (*ca*. 3773956 occupied autonomous fractions [227]). The new annual theoretical values for HDRC, CDRC, and DWDRC, for Portugal mainland usual residence building stock in 2010 are 80313, 6006 and 31631 GWh/year, respectively.

3.5 Estimation of the gap of the residential building stock for space and water heating

In this section, two main energy use gaps will be computed and named as 'reference' as the theoretical energy demand under reference conditions was used as the 'majorant' for thermal comfort conditions. In this case, the HDRC values were used for the space heating, and the DWDRC for the domestic hot water.

3.5.1 Top-down estimation of actual energy use for heating, cooling and domestic hot water

After the bottom-up assessment of the annual theoretical HDRC, CDRC and DWDRC, it is now intended to obtain a top-down value from the national energy balance for comparison purposes. This can be done combining the statistics of the 2010 Portugal mainland national energy balance [228] with estimates of the 2010 breakdown of the energy use in the residential sector [227], as represented in Figure 16.

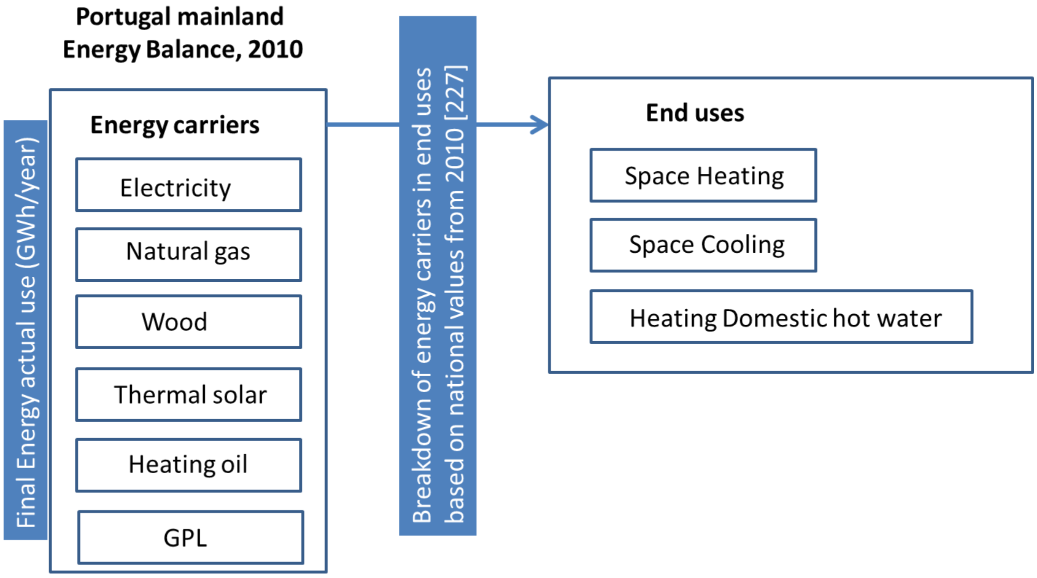

Figure 16. Schematic representation of the methodology for the disaggregation of actual energy use per end uses (final or 'delivered' energy).

The total actual use of 'final' energy for space heating, domestic water heating and space cooling for Portugal mainland usual residence building stock in 2010 is presented in Table 5. The end uses for cooking, equipment and lighting were not computed as they are out of the scope of this work. The total values obtained are similar to those reported in [227], based on inquiries to 7468 Portuguese homes: 6289 vs 6194 GWh/year for space heating, 157 vs 151 GWh/year for space cooling, and 7046 vs 6464 GWh/year for water heating. Still, the first values were considered more appropriate for calculations as they came from a top-down disaggregation, while the latter ones came from a bottom-up collection [227].

Table 5. Actual energy use ('final') of the Portugal mainland usual residence building stock for heating, cooling and DHW in 2010, disaggregated per vectors and end uses.

Actual energy use ('final' or 'delivered')	Space heating (GWh/year)	Domestic hot water (GWh/year)	Space cooling (GWh/year)
Electricity	897	230	157
Wood	4218	479	0
Natural gas	109	2157	0
Thermal solar	19	203	0
Heating oil	877	572	0
GPL	168	3405	0
Total (GWh/year)	**6289**	**7046**	**157**

The values of Table 5 are presented in terms of 'final' energy, but those of HDRC and CDRC of section 3.4 are presented in terms of 'useful' energy. It is necessary to convert the values presented in Table 5 to 'useful' energy to enable a comparison. Considering that ADENE's EPC´s database of 2012 lack of data in what regards heating equipment's efficiencies, average conversion efficiencies for heating were assumed from references: 100% for electricity, 87% for natural gas, 89% for GPL and heating oil and 40% for wood (resulting from a weighted mix between of open fireplaces and closed fireplaces) [214,229–231]. The actual 'useful' energy use values for space heating and space cooling for the Portugal mainland usual residence building stock in 2010 were thus estimated to be 3632 and 157 GWh/year, respectively.

3.5.2 Reference heating gap for space and domestic hot water

Table 6 shows a comparison between the 2010 theoretical energy demand under reference (´stringent´) conditions computed in section 3.4, and the estimated energy actually delivered for the stock of usual residences of Portugal mainland in 2010 computed in section 3.5.1. It should be noted that space heating and cooling demand are compared in terms of 'useful' energy, whereas domestic hot water is compared in terms of 'final' energy.

Table 6. Comparison between the annual theoretical energy demand under reference conditions ('stringent') and the estimated energy actually 'delivered' for the stock of usual residences of Portugal mainland for 2010.

End uses	Theoretical energy demand under reference ('stringent') conditions	Actual energy use
Space heating demand (GWh/year)	80313	3632
Space cooling demand (GWh/year)	6006	157
Domestic hot water demand (GWh/year)	31631	7046

The 'reference heating gap' is defined as the percent difference between the theoretical heating energy demand under stringent thermal comfort conditions (GWH/year) and the energy actually used (GWh/year) for space heating, for the existing residential building stock, as expressed in Eq. 3.2 (see also Figure 1, section 1.2). A similar procedure can be applied to estimate the 'reference heating gap' for domestic hot water. The value for cooling is not computed because it has been demonstrated that indoor temperatures well above 25ºC can be compatible with thermal comfort according to the adaptive comfort standard [232].

$$Reference\ heating\ gap = \frac{THD_{s.t.c.c.} - AEU}{THD_{s.t.c.c.}} \times 100 \quad [\%] \qquad \text{Eq. 3.2}$$

where $THD_{s.t.c.c.}$ is the theoretical heating energy demand under stringent thermal comfort conditions (GWh/year) and AEU is the actual energy use (GWh/year).

Using the values represented in Table 6, the resulting value for 'reference heating gap' for space in 2010 is 95%, while the value for water heating for the same year was 78%. This means that the actual space heating usage in reference to the theoretical value under reference conditions for that year is only 5%, which is even lower than the 10% assumed in the calculation of the primary total energy demand in the RCCTE regulation [72]. The domestic water heating usage is 22% of the theoretical value estimated under reference conditions, very far from the 100% assumed in the same regulation.

The differences found are very large, much beyond of what could be explained only by the lack of precision of the calculation procedure of the thermal performance assessment (either heating patterns (i.e., occupant behaviour), or other parameters assumed as reference values), or by the assumptions in the top-down breakdown of the national energy balance data.

3.6 Conclusions

This chapter has performed a preliminary assessment of the 'reference heating gap' and characterized the thermal performance of the residential building stock in Portugal mainland, making use of the Portuguese EPBD-derived EPC database.

Overall, this chapter showed that national databases of buildings energy certification schemes can be extremely useful in obtaining relevant insights on the thermal performance of the existing residential building stock. They can allow the identification of the most critical slots of building stock (e.g. in terms of type, age and region), and they can also assist analyzing to what extent the historical evolutions are justified by a natural phenomenon or by the effect of regulations. Furthermore, if combined with top-down energy balances, they can enable the estimation of the energy use gaps, which can be relevant both for health and energy policies.

For the specific case of Portugal, the results show that the thermal performance of buildings progressively improved caused by a mix of accelerations pushed essentially by natural market evolution, spill-over effects (as that of the 1960's) and regulations (as that after 2006). Despite the improvements, it is worth mentioning that the absolute values of theoretical heating energy demand computed under reference conditions (HDRC) for new buildings are far from the near-

Passivhaus levels implicit in the concept of near zero energy building required by the EPBD recast [7]. Results show that the majority (about 80%) of the building stock has theoretical HDRC values higher than 100kWh/m^2.year, even in a 'mild climate'.

The work also compared the estimated theoretical energy demand under stringent thermal comfort conditions with the estimated actual energy use for space and water heating, for the Portugal mainland residential building stock in 2010. The percent difference between the theoretical and the actual energy use values is referred as 'reference heating gap'. The results revealed gaps in 2010 of 95% and 78% for space and water heating, respectively. This means that occupants in Portugal mainland in 2010 used only 5% of the energy that they would need to maintain the whole dwelling at all time at a minimum of 20ºC during the winter season and, only 22% of the energy needed for one daily bath of 40 liters at 60ºC per person.

Following the empirical evidence from other geographical contexts [20,46], and specially giving attention to the generalized Portuguese cultural aspect of not valuing thermal comfort, such differences (gaps) are probably in a large extent due to differences in occupant behavior. It is a fact that occupants do not require their homes to be permanently to a minimum of 20ºC during the whole winter/heating season, nor to a maximum of 25ºC during the summer/cooling season, neither require a bath of 40 liters of water at 60ºC per day [105,232], in order to achieve levels of thermal comfort satisfaction. Nevertheless, it does not mean that the gap is not associated still to a level of 'deficit of comfort'. Actually, there are very few studies on determining whether the difference between the 'theoretical' and the 'actual' is part the expression of the difference between reference and actual values for heating patterns, or other parameters, or if it is also the expression of a 'deficit of comfort'. The suspicion that there could be occupants living in poor indoor environment conditions in residential buildings in Portugal during the winter season, lead one to conclude that the gaps reported in section 3.5.2 may be also regarded as an indicator of the later.

Further studies, involving statistically meaningful field monitoring of indoor temperatures, could contribute to provide with insights on this matter (chapter 4). Also, a more relaxed value of 'theoretical heating energy demand under thermal comfort conditions' (*(2)* in Figure 1, 1.2) is computed to reduce the gap that is explained by differences between reference and actual values for heating patterns (i.e, occupant behaviour). An estimation of the 'heating gap' is presented in chapter 5.

CHAPTER 4

CHARACTERIZING AND PREDICTING INDOOR TEMPERATURES IN RESIDENTIAL BUILDINGS

Empirical data for residential indoor temperatures and heating patterns have important implications for policymakers and energy demand models developers. This chapter explores the results from a monitoring campaign to the residential building in Northern Portugal to assess the actual indoor temperatures and to understand the heating patterns in the residential buildings in Northern Portugal during the winter season. In addition, the study develops a model to predict indoor temperatures, identifying its main determinants.

These objectives provide better insights on indoor temperatures and heating patterns assumptions and enable more accurate and robust energy modeling/planning and energy savings predictions resultant from energy efficiency programmes. These insights can also have important implications for policymakers in the establishment and development of programmes to improve indoor thermal comfort and health conditions.

Chapter 4 is composed by the following sections. Section 4.1 presents the procedures for data collection and selection of the sample. Section 4.2 characterizes the indoor monitored temperatures, whereas section 4.3 addresses the methodology behind the modeling of actual indoor temperatures. Section 4.4 presents the results of the predicting indoor temperature models. Finally, section 4.5 presents the main conclusions of the study developed under this chapter.

4.1 Data collection and sample

4.1.1 Selection of households

The monitoring campaign occurred in four locations situated in the Northern Portugal. The locations were selected aiming to capture a large range of Heating Degree Days (HDD) [233] and purchase power values (p.p. relative to the national average value of 100%) [234]. The four locations that best fitted these criteria are Porto (1610 HDD, 161.65% p.p.), Ponte de Lima (1790 HDD, 64.97% p.p.), Sabrosa (2380 HDD, 60.31% p.p.), and Bragança (2850 HDD, 96.47% p.p.). Table 7 presents the main characteristics of the four locations (mean height, mean low temperature, mean high temperature, HDD and purchasing power). Figure 17 shows their geographical location.

Table 7. Main characteristics of the four locations studied.

Locations	Mean height (m)[c]	T. mean low (ºC), January	T. mean high (ºC), January	HDD	Purchase power (%)
Porto	83	5.0[a]	13.5[a]	1232	161.7
Ponte de Lima	19	6.3	13.7	1256	65.0
Sabrosa	579	3.8	9.9	1764	60.3
Bragança	690	0.2[b]	8.8[b]	2029	96.5

[a]Reference: [235];
[b]Reference: [236];
[c]Reference: [237].

In order to distribute the temperature dataloggers to a large number of households, this study accounted with the participation of four schools (one school in each location). The schools were selected according to the number of students, the type of surrounding dwellings and their will and availability to cooperate.

For the purpose of selecting a representative sample of households, the students were given a short survey between September and October 2013. The surveys included the following items: location, dwelling's age of construction, household´s income, whether if it is an apartment or a house, type of household, size of the household and typical dwelling occupation schedules. Based on the analysis of the surveys received, the classrooms were selected in accordance to their representativeness, and the final set of households willing to participate in the monitoring campaign was 141: 41 households in Porto, 42 in Ponte de Lima, 27 in Sabrosa and 31 in Bragança.

Figure 17. Geographical location of Ponte de Lima, Porto, Bragança and Sabrosa.

4.1.2 Indoor and outdoor temperature dataset

The indoor air temperatures were measured using portable temperature and humidity dataloggers, which have an accuracy of ±0.5ºC and a resolution of 0.5ºC for temperature, and ±3% and 0.5%, respectively, for relative humidity [238]. Two dataloggers were used in each of the 141 dwellings monitored. One was used to monitor the living room (or other common room frequently used, i.e. kitchens) and the other was placed in the student´s bedroom. The dataloggers were located approximately 1.5m above the floor level, taking care that they were neither obtrusive nor hidden behind furniture or exposed to direct sunlight (as represented in

Figure 18). The dataloggers operated with long-life batteries and were able to hold data for the entire analyzed period.

The temperatures were measured and stored every half an hour from 27th November 2013 to 28th February 2014 (i.e., 94 days). Thus, about 4.500 data-points were registered for each monitored room. At the end of the monitoring campaign, the half-hourly raw data was read and processed to daily basis. In particular, the collected data was analyzed under two perspectives: mean indoor temperatures at the 24h period, and mean indoor temperatures at the occupied period (from 22:00 to 08:00 for the bedrooms, and from 18:00 to 24:00 for the living rooms).

Figure 18. Example of a datalogger placed in a household bedroom.

Concerning the outdoor temperatures, four dataloggers (one in each location analyzed) were used to measure the local outdoor temperatures on a half-hourly basis. In particular, the dataloggers were placed outside the schools that agreed to participate in the study. Similarly to indoor temperature, the collected data on outdoor temperatures was analyzed on a daily basis under two perspectives: mean outdoor temperatures at the 24h period, and mean outdoor temperature at the occupied periods.

4.1.3 Socio-economic factors and building characteristics dataset

Data related to socio-economic factors and building characteristics were collected from a detailed survey (Appendix B) distributed to households that participated in the study. The survey, filled in by the household representant, included questions related to the following aspects: educational attainment, number and type of household, monthly net income, and building and heating equipment properties. The main items inquired in the survey for the socio-economic factors and building characteristics are presented in Table 8.

Table 8. Variables and its categories.

Variable name	Items inquired	Categories
	Building characteristics	
Age of construction	*Age of dwelling´s construction*	[Until 1919-1945; 1946-1960; 1961-1970; 1971-1980; 1981-1990; 1991-2000; 2001-2011]
Apart./house	*Apartment or house*	[Apartment; house]
Type dwelling	*Type of dwelling*	[Detached-house;semi-detached house; terrace-house; 1 façade to exterior]
Apart. Position	*Position of the apartment in the building*	[Not applicable; ground-floor; first floor over garage/store; between floors; last floor]
Wall thickness	*Thickness of external wall*	[<20 cm; 20-40cm; >40 cm]
Air cavity wall	*Existence of air cavity on external wall*	[Yes; No]
Wall insulation	*Existence of external wall insulation*	[No; yes, until 4cm; yes, over 4cm]
Window frame	*Type of window frame*	[Aluminium; Wood; PVC]
Type w. glazings	*Type of window glazing*	[Single; Double]
Window orient. (bed./liv.)	*Bedroom/living room´s window orientation*	[North; East; South; West]
Roof insulation	*Existence of roof insulation*	[No; yes, until 4cm; yes, over 4cm]
Total area	*Total dwelling area (m^2)*	[<30; 30-49; 50-79; 80-99; 100-119; 120-149; 150-199; 200-249; 300-349; >349]
Area (bed./liv.)	*Bedroom /living room area (m^2)*	[0-15;16-20;21-25;26-30;>30]
No. Bedrooms	*No. of bedrooms in the house*	[T0; T1; T2; T3; T4; T5; T6; T7; >T7]
Category equip (bed./liv.)	*Categories of heating equipment existent in the bedroom/living room*	[None; Portable; Fixed]
Type equip (bed./liv.)	*Type of heating equipment existent that supplies heat to the bedroom/living room*	[None; electrical radiator; thermoventilator; open fireplace; closed fireplace; air conditioner; gas boiler; diesel boiler; wood boiler; salamander; gas heater]

Table 8. Variables and its categories (continuation).

Variable name	Items inquired	Categories
	Socio-economic factors	
Rep. school.	*Maximum schooling of household representants*	[Primary school; secondary education; degree; master; PhD]
Household size	*No. of people living in the dwelling*	[0-2; 3-4; 5-6; 7-8]
Household	*Type of household*	[Children, adults and older people; children and adults; adults (>14-65); adults and older people; children and older people]
Min. occp. Day	*Minimum occupied period during the day*	[Always at home, except evening; always at home, except in the afternoon; always at home,, except in the morning; just in the evening; just in the afternoon; just in the evening; just in the morning; all day long]
Profe. Situation	*Professional situation of active households*	[Mostly employed; half employed; no active households; all unemployed; all employed; mostly unemployed]
Tenure	*Type of tenure*	[Landlord rented housing; cooperatives rented housing; Private housing with bank loans; Private housing with no bank loans]
1 Person bed.	*Just 1 person sleeping in the bedroom*	[Yes; No]
Monthly net income	*Monthly net income (€/month)*	[0-350; 351-750; 741-1250; 1251-2000; 2001-3000; 3001-5000; >5000]
Value comfort (bed./liv.)	*If occupants value comfort in bedrooms/living rooms*	[Does not value comfort; value comfort]

Table B.1 and Table B.2, in Appendix B, report some of the characteristics of the sample analyzed based on the responses in the survey related to socio-economic aspects and building characteristics, respectively. From the responses gathered, it was possible to infer that the majority of the households analyzed were composed by 3 to 4 people (76%) and had all the active households employed (67%). Around 45% of the households were in the income range between 751 and 2000€ per month. The majority of the dwellings were houses (57%) and a high portion was constructed between 2001 and 2011 (32%) and in the decade of 1990 (28%). The presence of heating equipment varies a lot, being the electric radiator the most common equipment (16%). Salamander (11%), open fireplaces (10%) and closed fireplaces (10%) were also commonly presented.

Data related to heating patterns, adaptation strategies and thermal comfort preferences was collected from a detailed survey distributed to households at the end of the monitoring campaign (Appendix B). To evaluate the heating patterns the survey included questions related to the following aspects: length of heating period during the winter season, length of heating period during the day and type of heated rooms. To evaluate the thermal adaptation strategies households were asked about which adaptation measures were taken during the monitoring campaign. Households were also asked to scale their thermal comfort preferences in accordance to indoor temperatures. Finally, unmet but desired heating patterns were evaluated by asking households about their preferences on the length of the heating period during the winter season and during the day, as well as the type of rooms that they would like to have heated.

In what regards heating patterns, namely the length of the heating period (in number of months) of the bedrooms, the majority of households (54%) mentioned 0 (i.e., 'no heating') or 1 month. However, for living rooms, a high percentage of the households (45%) responded 4 to 5 months. Also, concerning the length of the heating period during the day, around 49% of the households mentioned having heated the bedrooms for only less than half of the day and 37% mentioned not having heated the bedrooms at all. Table 9 and Table 10 present the length of the heating period for bedroom and living rooms during the winter season and during the day, respectively.

Table 9. Length of heating period during the heating period (in terms of number of months) for bedroom and living room.

Length of heating (no. of months)	Bedroom	Living room
0-1	53.7%	28.6%
2-3	10.5%	8.8%
4-5	24.2%	45.1%
6-7	11.6%	17.6%
Total	100.0%	100.0%
Total answers	**95**	**91**

Table 10. Length of heating period during the day for bedroom and living room.

Length of heating	Bedroom	Living room
No heating	34.1%	17.4%
Less than half of the day	48.8%	72.0%
More than half of the day	8.5%	3.8%
All day	8.5%	6.8%
Total	100.0%	100.0%
Total answers	**129**	**132**

Concerning the type of heated rooms, 33% of the households confirmed having heated the living room, bedrooms, kitchen and bathrooms; 12% only the living rooms; 8% the living room and bedrooms and other 8% the living room, the bedrooms and bathrooms (see highlighted column in Table B.3, Appendix B).

In terms of unmet but desired heating patterns, 48% of the households answered that they would prefer to have heated the living room, kitchens, bathrooms and bedrooms, 12% living room, kitchen and bedrooms, and 12% just living rooms and bedrooms (see highlighted column in Table B.4, Appendix B). 29% of the households answered that they would prefer to have heated for longer periods during the winter season (see highlighted column in Table B.5, Appendix B) and 54% also admitted that they would prefer to have heated for longer periods during the day (see highlighted column in Table B.6, Appendix B).

88% of the households assumed to have embraced adaptation strategies, such as resorting to warmer blankets, clothing adjustment or hot drinks. Nevertheless, when asked to scale their thermal preferences in accordance to the indoor temperatures registered during the monitoring campaign (see highlighted column, Table B.7, in Appendix B) the majority of households living in Porto (81%), Bragança (61%), Sabrosa (63%) answered that they would prefer warmer temperatures. In turn, the majority of households in Ponte de Lima (54%) were satisfied with the indoor temperatures. From those resorting to thermal adaptation strategies 68% pointed out their preference for warmer temperatures.

Table 11 shows a comparison between the sample analyzed and the values of Northern Portugal [239]. This table presents a subset of indications as these are the only data available in the National Institute of Statistics. According to this table, it is possible to verify that the sample of households selected for this study represents reasonably the dwellings of the Northern Portugal (see the similar values of % Northern Portugal and % sample reported on the table).

Table 11. Comparison between sample and values of the Northern Portugal.

	% N.Portugal	% Sample		% N. Portugal	% Sample
No. of households (N=139)			Tenure (N=136)		
Ponte Lima	11%	30%	Rented to landlord	18%	18%
Sabrosa	2%	19%	Rented to state/cooperatives	3%	10%
Porto	76%	29%	Pay provision to the bank	30%	30%
Bragança	11%	22%	Own housing	49%	42%
Building age (N= 107)			No. of bedrooms (N=112)		
Until 1919 to 80	41%	9%	0 bedrooms	0%	0%
1981-90	19%	12%	1 bedroom	2%	4%
1991-00	23%	36%	2 bedrooms	8%	7%
2001-11	16%	42%	3 bedrooms	26%	15%
Apartment or house (N=137)			4 bedrooms	34%	24%
Apartment	45%	41%	5 bedrooms	14%	16%
House	55%	59%	6 bedrooms	7%	15%
			7 bedrooms	4%	7%
			>7 bedrooms	4%	12%
Household annual net income (€/year) (N=116)			Type of equipment (N=101)		
9634	20%	20%	Ar conditioning	----	1%
14800	20%	32%	Gas boiler	0%	10%
19061	20%	23%	Diesel boiler	0%	5%
25770	20%	16%	Wood & salamander boiler	5%	25%
49539	20%	9%	Open fireplace	19%	14%
			Closed fireplace	8%	14%
Employment status (N=134)			Eletric radiator & thermoventil.	31%	27%
None active	27%	3%	No heating	12%	5%
Half employed	7%	18%			
Mostly employed	3%	1%			
All employed	56%	70%			
Mostly unemployed	1%	1%			
All unemployed	5%	7%			

4.2 Characterization of indoor temperatures

4.2.1 Overview of daily mean outdoor and indoor temperatures

Porto has a Mediterranean climate, in particular, winter outdoor temperatures typically range between 5ºC and 14ºC, rarely dropping below 0ºC. It is also typical during this season that rainy periods alternate with cooler days and clear skies [240]. Ponte de Lima, located at north of Porto, but still near the Atlantic coast, presents similar outdoor temperature ranges [241]. In turn, Sabrosa is situated in the interior of the country and surrounded by mountains and presents a sharper winter with temperatures ranging from 4ºC and 10ºC [242]. In Bragança, the winter is long, cold and wet with mean min values frequently below 0ºC and mean high values of 10ºC [243]. Table 12 presents the typical daily mean outdoor temperature according to the historical records [235,236] and to the values for the four locations gathered from the monitoring campaign. It can be observed that the monitored winter of 2013-2014 was slightly milder than typical years. The difference is particularly evident in terms of the mean low temperature (e.g., in Bragança, it was over the average by +2.9ºC).

Table 12. Daily mean outdoor temperature records and monitored values for the four locations.

Locations	Winter period	Mean high (ºC)	Daily mean (ºC)	Mean low (ºC)
Porto	Typical year	14	10	6
	Monitored period	**14**	**11**	**8**
Ponte de Lima	Typical year	14	10	7
	Monitored period	**14**	**10**	**8**
Sabrosa	Typical year	11	7	4
	Monitored period	**9**	**7**	**5**
Bragança	Typical year	10	5	1
	Monitored period	**13**	**8**	**4**

In what concerns the daily mean indoor temperatures, there is no typical value for the dwellings analyzed. The daily mean bedroom temperatures for the occupied period, were higher than 20ºC in only 4% of the dwellings, between 18ºC to 20ºC in 6% of dwellings, between 14ºC and 16ºC in 31% of the dwellings, and below 14ºC in 35% of the dwellings (with 2% of the dwellings exhibiting temperatures lower than 10ºC). The daily mean indoor temperatures for the 24h period present a similar distribution.

The daily mean living room temperatures in the 24h period were maintained in the range of 14ºC to 16ºC for 29% of dwellings, and between 16ºC and 18ºC for 27% of dwellings. In 20% of dwellings, temperatures were above 18ºC (with 6% above 20ºC). There are still 24% of households with living room temperatures below 14ºC, from which 5% were in the range 10ºC and 12ºC, and 1% reaching less than 10ºC. Regarding the occupied period, the large shares lie between 16ºC and 18ºC (26% of dwellings), 14ºC and 16ºC (24% of dwellings), 18ºC and 20ºC (18% of dwellings) and above 20ºC (14% of dwellings). Still, there are dwellings registering daily mean temperatures between 10ºC and 12ºC (4% of dwellings) and lower than 10ºC (1% of dwellings).

Table 13 presents an overview of the daily mean indoor temperatures for bedroom and living room, for the occupied and 24h period. Overall, the results from Table 13 show that indoor temperatures are significantly below the levels putatively recommended by the WHO below (21ºC at living rooms, and 18 ºC in the other occupied rooms) [244] .

Table 13. Daily mean indoor temperatures for bedroom and living room.

		Bedroom					Living room				
		Sabrosa	Bragança	Pt. de Lima	Porto	All locations	Sabrosa	Bragança	Pt. de Lima	Porto	All locations
24h period	Mean daily	14	16	14	16	15	16	17	15	16	16
	Standard deviation	3.3	3.0	2.9	2.3	3.1	3.9	3.0	3.0	2.4	3.2
	Mean high	15	17	15	17	16	19	19	16	17	18
	Mean low	12	15	13	15	14	14	16	14	16	15
	30% Percentile	12	14	12	15	13	14	15	13	15	14
	70% Percentile	15	18	16	17	16	18	19	16	17	17
Occupied period	Mean daily	14	16	14	16	15	18	17	15	17	17
	Standard deviation	3.4	3.0	3.0	2.4	3.1	4.4	3.1	3.3	2.4	3.4
	Mean high	15	17	15	17	16	19	18	16	17	17
	Mean low	13	15	13	16	14	16	17	15	16	15
	30% Percentile	12	14	12	15	14	15	16	14	16	14
	70% Percentile	15	18	16	17	16	20	19	17	18	18

It should be noted that almost 30% of the time, households in the two poorest locations (Ponte de Lima and Sabrosa) have bedroom temperatures lower than 12ºC even in the occupied period.

A second major conclusion withdrawn from Table 13 is that living rooms are usually warmer than bedrooms by a difference of 1.7ºC in the occupied period and by 1ºC in the 24h period. Actually, in contrast to 24% of the households, 42% have affirmed that there is no need to have temperatures higher in the bedroom than in the living room.

From Table 13, it is also evident that there is no considerable difference between the daily mean bedroom temperatures in the occupied (15ºC) and 24h period (15ºC). However, for the living room, the difference is almost 1.0 ºC between the two different periods. For example, in Sabrosa, the difference in living room temperatures is quite evidential (18ºC and 16ºC for the occupied and 24h period, respectively). In addition, the mean living room temperature at the occupied period is, on average, 3.7ºC warmer than bedroom temperatures, which can be an indication that those rooms are highly valued during that period.

A paired sample t-test was conducted in order to check if there are statistically significant differences between the daily mean indoor temperatures of 'all locations' (see seventh and twelfth columns in Table 13) in the living rooms and in the bedrooms, during the occupied and 24h period.

Table 14 presents the results obtained in the four paired sample t-tests conducted. The results indicated that the differences are statistically significant (p-values < 0.0001). This suggests that a separate analysis should be done for mean bedroom temperature in the occupied period and 24h period, and for the mean living room temperature in the occupied period and 24h period. Besides the existence of a significant difference between daily mean bedroom temperature in the occupied and 24h period, the focus will be on the occupied period hereafter because it is believed that a mean difference of 0.155 in the Celsius scale might not have an impact on the thermal comfort of occupants. Results from Table 14 also indicate that the difference between mean indoor bedroom and living rooms´ temperatures is significant either in the 24h period or during the occupied period.

Table 14. T-tests.

	T	Df	p-value	Mean Difference
Bedroom (24h vs occ. period)	-8.978	140	.000	-.155
Living room (24h vs occ. period)	-9.831	139	.000	-.750
24h period (bed. vs liv.)	-6.383	139	.000	-1.05
Occupied period (bed. vs liv.)	-7.624	139	.000	-1.65

Comparing the mean indoor and outdoor temperatures, it is possible to infer that lower outdoor temperatures do not necessarily imply lower indoor temperatures. For example, when comparing the daily mean temperature values from Table 12 and Table 13, it can be observed that although Bragança and Porto present similar indoor temperatures, the outdoor temperatures in Bragança are lower than in Porto. Other factors may have therefore contributed to the explanation of indoor temperatures. In order to depict in detail the nature of these relationships, an advanced linear regression between indoor temperatures, socio-economic factors, building characteristics and climatic factors is developed in sections 4.3 and 4.4.

Figure 19 presents a closer look to the time distribution of the temperatures for the period analysed. Analysing Figure 19, it can be verified that indoor bedroom and living room temperatures suffer a decrease from the early morning (0:00 to 08:00) to the afternoon (08:00 to 18:00), and then become higher in the evening (18:00 to 24:00), which is commonly the warmest period of the day indoors. Space heating is likely the main explanation for this phenomenon, but solar heat gains combined with thermal inertia (i.e., effects of heat storage), as well as, indoor heat gains, can also be an influential factor. To note that in this work it was considered, for the living rooms, the occupied period from 18:00 to 24:00, and for the bedrooms, from 22:00 to 08:00. The bedroom indoor temperatures are actually slightly lower during the sleeping period than during the period between 18:00 and 24:00. This means that many occupants might have turned heating off before sleeping. In turn, it seems that occupants preferably heat their living rooms during the occupied period. For better insights, Figure B.1 presents the hourly mean indoor bedroom and living room temperatures for all the locations.

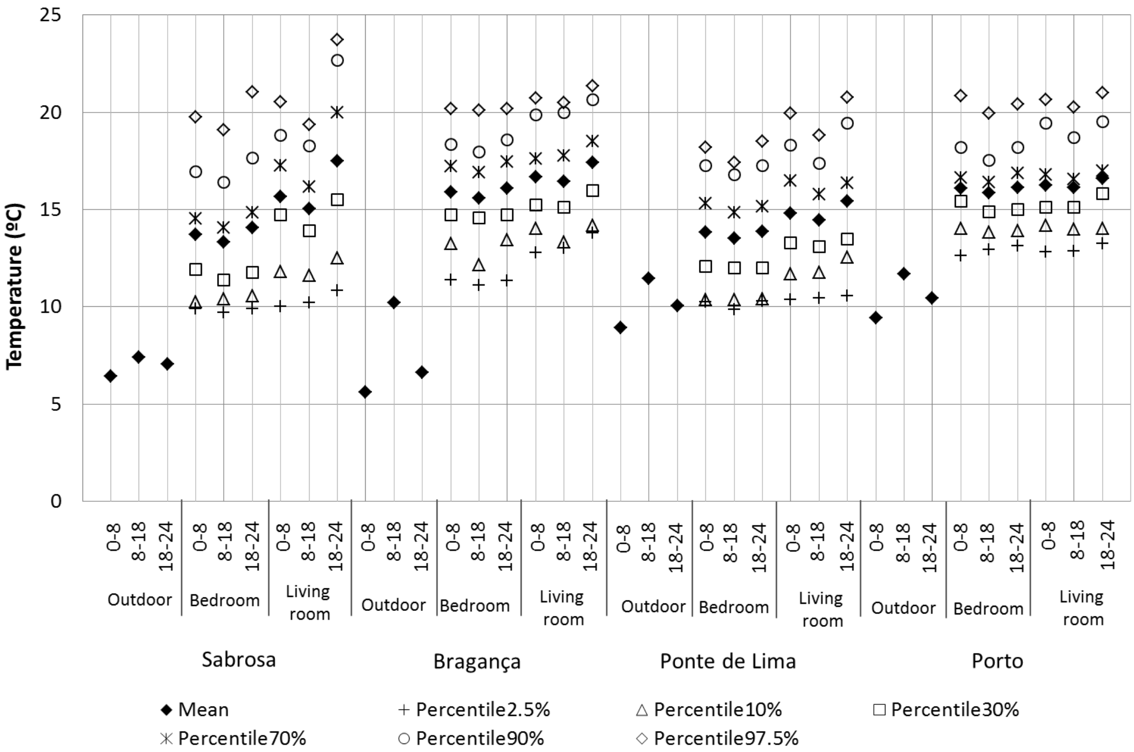

Figure 19. Distribution of the winter daily outdoor and indoor bedroom and living room temperatures for Sabrosa, Bragança, Ponte de Lima and Porto.

4.2.2 Characterization of daily mean indoor and outdoor temperatures profile over time

The daily mean bedroom temperature profile for the occupied period is given in Figure 20 and the living room temperature profiles are given in Figure 21 and Figure 22, for the occupied and 24h period, respectively. Figures reveal that the amplitude range of bedroom temperatures in the occupied period is higher for Ponte de Lima and Sabrosa. In turn, Porto and Bragança maintained, on average, a more constant temperature throughout the winter season. In general, the highest daily mean bedroom temperature peaks were found to occur in January, whereas the lowest occurred in December and February. Nevertheless, according to Table 15, the main difference between outdoor and indoor bedroom temperatures during the occupied period (22:00 to 08:00) occurred in December.

Concerning the living room, the amplitude of daily mean temperature is smaller than the mean bedroom temperatures, especially for Sabrosa. The highest daily mean temperature peaks were found to occur in January and December, for Sabrosa, Ponte de Lima and Porto, and in January and February for Bragança. Like bedrooms, the main difference between outdoor and indoor temperatures during the occupied period (18:00 to 24:00) in Sabrosa, Ponte de Lima and Porto occurred in December, and in January in Bragança.

In summary, two main typical indoor temperature profiles over time were observed. One is characterized by fairly higher constant temperatures, with few oscillations over time. The other has higher temperature amplitude and is more prone to the outdoors´ influences. The latter might be a consequence of several situations, including lower heating practices, lower thermal performance of buildings and/or heating systems. Also, according to Table 15, it seems that the majority of the households heat their homes preferably in December (i.e., the major differences between indoor /outdoor temperatures occurred in December).

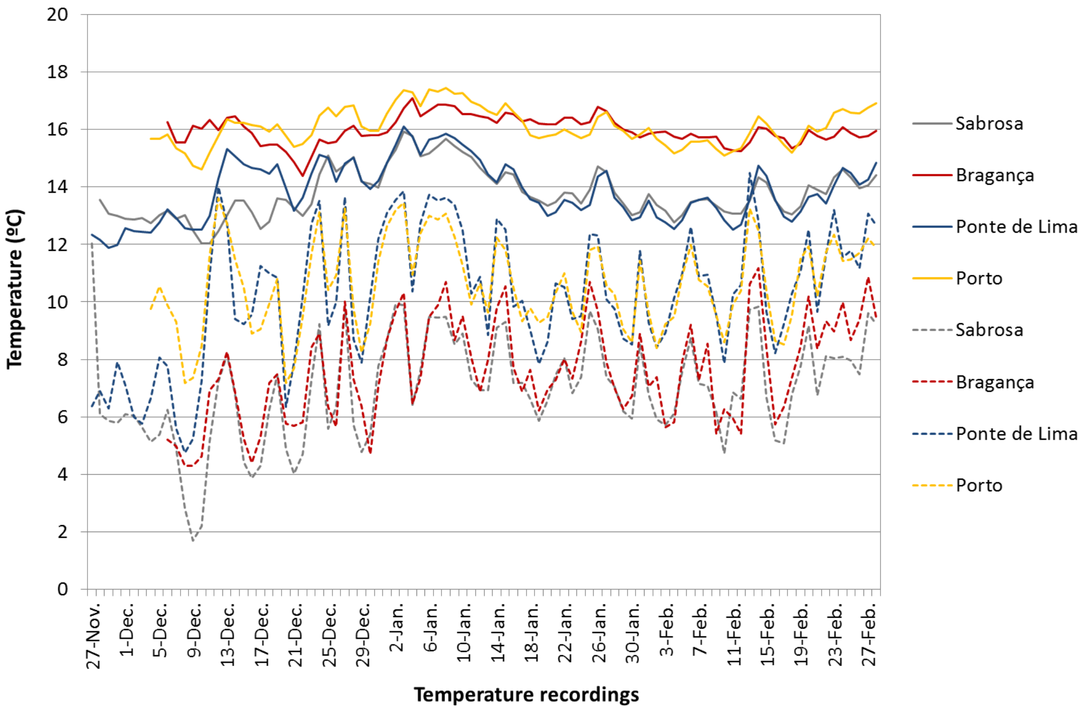

Figure 20. Daily mean bedroom temperature profile (continuous lines) vs daily mean outdoor temperature profile (dotted lines) for all the locations, at occupied period.

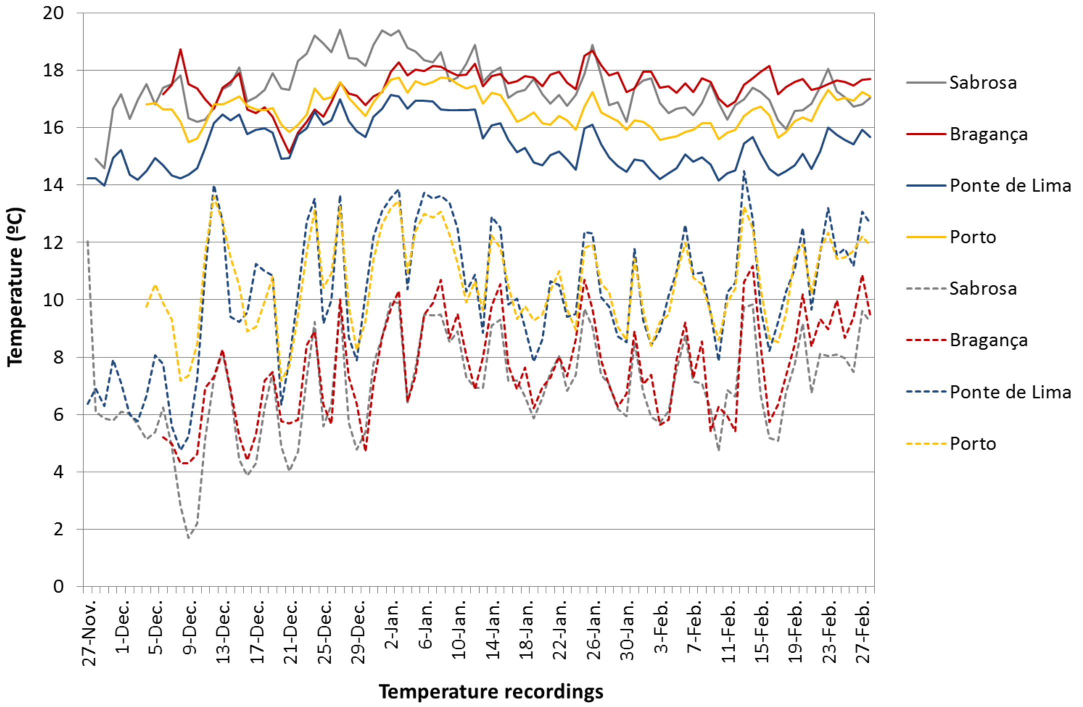

Figure 21. Daily mean living room temperature profile (continuous lines) vs daily mean outdoor temperature profile (dotted lines) for all the locations, at occupied period.

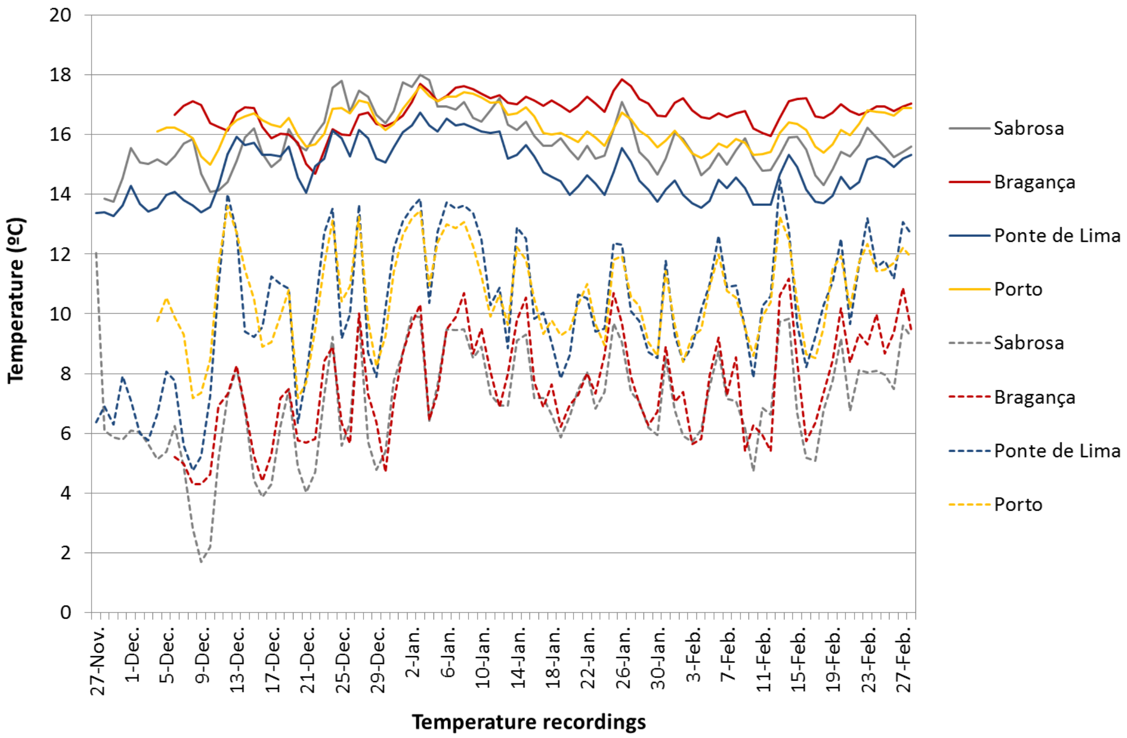

Figure 22. Daily mean living room temperature profile (continuous lines) vs daily mean outdoor temperature profile (dotted lines) for all the locations, for the 24h period.

Table 15. Daily mean indoor and outdoor temperatures for all locations of study, for bedroom (bed.) and living rooms (liv.), for the respective occupied period.

	Sabrosa (ºC)				Bragança (ºC)				Ponte de Lima (ºC)				Porto (ºC)			
	Out	Bed.	Out	Liv.	Out	Bed.	Out	Liv.	Out	Bed.	Out	Liv.	Out	Bed.	Out	Liv.
December	5	13	6	18	4	16	5	17	8	14	9	16	9	16	10	17
January	8	14	8	18	7	16	3	18	10	14	11	16	10	17	11	17
February	7	14	7	17	6	16	7	18	10	14	10	15	10	16	10	16

4.2.3 Thermal comfort levels

Several studies investigated indoor temperatures in the residential sector and the perception of thermal comfort of the households to their indoor environment [13,30–51]. The International Standard ISO 7730 [245] uses the Predicted Mean Vote (PMV) and the Predicted Percentage Dissatisfied (PPD) indices (Fanger´s comfort indices) to predict the thermal sensation of people exposed to moderate thermal environments, as well as to specify acceptable thermal environmental conditions for comfort [36,109]. The static thermal comfort model described in ISO 7730 is often criticized due to the little recognition of the outdoor climatic context and personal requests [246].

There are several adaptive comfort models [38,247] that estimate the neutral temperatures (temperature that gives a neutral thermal sensation in the indoor environment, i.e. neither of warmth nor of chill [248]) for certain outdoor conditions. The theoretical base of adaptive comfort models is the concept of adaptation [246] to thermal indoor conditions, which occurs in three ways: physiological, psychological and behavioural. The adaptive models were derived from statistical analyses of formalized interviews/surveys of occupants using physical data gathered by monitoring real buildings with regular operation conditions. In general, the studies point for a linear relationship between the theoretical indoor comfort temperature and the evolution of the outdoor temperature. From the large number of models proposed in the literature, the American adaptive model and the European adaptive model gained an international consensus.

Both thermal comfort models are currently used in several studies [45,70,249]. The American adaptive model was developed by de Dear *et al.* [246] and was introduced for the first time in 2004 in the American standardization through a revision of the standard ANSI/ASHRAE 55 [250]. Its application is limited to 'naturally ventilated buildings', i.e., 'those spaces where the thermal conditions of the space are regulated primarily by the opening and closing of windows by the occupants' [250].

The European adaptive model was developed by Nicol and Humphreys [232] and was introduced in 2007 in the European standardization, within the standard EN 15251 [251]. EN 15251 limits the adoption of the European adaptive model to those 'buildings without mechanical cooling systems'. Both models can be employed when the functions used to represent the evolution of the outdoor air temperature fall inside specific applicability ranges. Outside such ranges, they are not applicable [252].

Table 16 shows the estimated indoor neutral temperatures based on Humphreys and Nicol (1998)´s adaptive comfort model (Eq. 4.1) [87] and the percent of times that these are achieved or exceeded in each location.

Humphreys and Nicol (1998)´s adaptive comfort model [87] for an unknown system (an average of all buildings):

$$T_c = 24.2 + 0.43(T_{out} - 22)exp - \left(\frac{T_{out} - 22}{28.284}\right)^2 \qquad [ºC] \qquad \text{Eq. 4.1}$$

where, T_c is the indoor comfort temperature (ºC) and T_{out} the monthly mean outdoor temperature (ºC).

Table 16. Indoor neutral temperatures according to Humphreys and Nicol model [87], and the percentage of time that these are achieved or exceeded in each location for bedroom (Bed.) and living rooms (Liv.). In the points marked with an *, the model was applied beyond the declared applicability range in terms of outdoor temperatures.

		Sabrosa			Bragança			Ponte de Lima			Porto		
		T (ºC)	Bed.	Liv.	T (ºC)	Bed.	Liv.	T (ºC)	Bed.	Liv.	T (ºC)	Bed.	Liv.
24h period	December	15*	34%	63%	16*	55%	59%	18*	12%	22%	18*	23%	30%
	January	17*	22%	46%	17*	51%	62%	19	7%	16%	19	14%	20%
	February	17*	14%	37%	17*	40%	54%	19	4%	11%	19	11%	15%
Occupied period	December	15*	50%	76%	16*	58%	68%	18	14%	29%	18	24%	35%
	January	17*	24%	62%	17*	53%	73%	19	8%	22%	19	18%	23%
	February	17*	16%	54%	17*	42%	66%	19	4%	17%	19	13%	18%

Depending on the month, the neutral temperatures ranged between 15 and 17ºC, 16 and 17ºC, and 18 and 19ºC for households living in Sabrosa, Bragança and in Ponte de Lima and Porto, respectively. Results indicated that indoor temperatures are far from the neutral temperatures (the closest are the living rooms at occupied period, especially in Sabrosa and Bragança) based on the Humphreys and Nicol (1998)´s adaptive comfort model [87]. Though, this is a general model that can only be considered for indicative purposes. The cultural aspect may be a key factor when considering the adaptation of Portuguese households to indoor temperatures.

4.2.4 Identification of heating patterns

Analyzing the mean temperature in each hour for the period studied, along with the responses to surveys regarding the length of heating period during the day (based on Table 10), it was possible to infer about the heating patterns for each dwelling.

Table B.8 and Figure B.2, in Appendix B, present the hourly mean bedroom temperature distribution for a sample of dwellings (i.e., 7 dwellings), the responses to surveys, and the corresponding inferred heating patterns. The distributions provided information on the hourly mean temperature patterns during the day. In the case of unclear patterns, the heating pattern was supported by the responses to surveys. In the case of ambiguous patterns with no responses, dwellings were not classified with a heating pattern (i.e., 'non-identified' pattern).

Taking this process to the 141 dwellings analyzed, Table 17 illustrates the heating patterns inferred ('no heating'; heating all day', 'heating during evening', 'heating all night' and 'other') and the corresponding share of each heating pattern.

Table 17. Distribution of heating patterns per location of study for bedroom and living rooms.

Heating patterns inferred	Bedroom	Sabrosa	Bragança	Pt. Lima	Porto	Living room	Sabrosa	Bragança	Pt. Lima	Porto
No heating	33%	44%	10%	44%	33%	18%	11%	0%	21%	32%
All day	9%	4%	21%	0%	11%	7%	0%	18%	0%	12%
During evening	49%	40%	55%	56%	42%	71%	85%	79%	76%	47%
All night	9%	12%	14%	0%	14%	3%	0%	4%	0%	9%
Other	0%	0%	0%	0%	0%	2%	4%	0%	2%	0%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
N inferred	**129**	**25**	**29**	**39**	**36**	**131**	**27**	**28**	**42**	**34**
Non identified	**12**					**9**				

For the bedrooms, the largest share of households (49%) exhibits the 'heating during the evening' pattern. This means that at least 49% of the households have heated their bedroom for some time just before going to bed. The 'no heating' pattern is also common for a high number of households (33%). For a 'free-running' building, indoor temperatures are a consequence of heat gained/stored from solar heating and occupants, offset by heat lost through the building fabric and by infiltration [10]. For the living rooms, it is possible to conclude that the share of the 'no heating' pattern (18%) is lower than the bedroom patterns, but the inverse occurs to the share of 'heating during the evening' pattern (71%). This is a clear indication that households heat more often the living rooms than the bedrooms. 53% of the households that have heated the living room only during the evening actually occupied their homes only at that period of time. The problem lies when there is still a great share of households (47%) with that heating behaviour but has at least one person staying home all day when no living rooms are being heated (see Table B.1, in Appendix B).

Regarding the expression of each heating pattern, for the bedrooms, per location, (presented in Table B.9, in Appendix B), Bragança is the location with the lowest share of 'no heating' pattern (7%), in contrast with Ponte de Lima (40%). Actually, Bragança is the location where more households heat their bedrooms all day long, followed by Porto. Similar conclusions can be applied to the heating patterns that characterize the living rooms.

4.3 Modeling indoor temperatures

4.3.1 Description of the statistical models

Three models were developed for the actual indoor temperatures of the residential building stock in Northern Portugal, taking the form of what is usually known in statistic sciences as 'prediction models'. Most building stock models would benefit from robust estimates of indoor dwelling temperatures [68]. In particular, the models will predict three models: the daily mean bedroom or living room temperatures for the occupied period, and the daily mean living room temperatures for the 24h period. Beyond the prediction purposes, the models will enable users to identify and quantify the importance of socio-economics factors, building characteristics and climate factors to explain indoor temperatures.

Following the approach proposed by Kelly *et al.* [68], the models developed were based on linear regression with panel-corrected standard errors. In particular, this statistical model enables users to account for the panel nature of the data gathered from the monitoring campaign, which covered 141 dwellings during a period of 94 days. It presents important benefits for modeling indoor temperatures over the standard linear regression as it enables users to control for heterocedasticity (each unit has its own variance) and contemporaneous correlation across units (each pair of units has its own covariance), instead of assuming that the errors are independent and identically distributed.

The general form of the model developed [253] can be presented as follows:

$$T_{it} = \alpha_0 + \beta_1(V_1)_{it} + \beta_2(V_2)_{it} + \dots + \beta_k(V_k)_{it} + \varepsilon_{it} \quad [ºC] \qquad \text{Eq. 4.2}$$

where T_{it} is the daily mean indoor temperature associated with unit (i.e., dwelling) *i (i=1,…,n)*, in day *t (t=1,…,s)*. It corresponds to the mean of the bedroom or living room temperature over 24h or over the occupied time period for a specific dwelling *i,* in a specific day *t*. V_k represents the variables *(k=1, …,k)*, related to socio-economic factors, building characteristics and climatic conditions (i.e., outdoor temperatures), and β_k represents the parameters to be estimated (i.e., coefficients of each variable); α is a constant term; ε_{it} is a disturbance that may be autocorrelated along *t* or contemporaneously correlated across *i* [253]. To run model (Eq. 4.2), STATA11 software was used, invoking the command *xtpcse* [253] using the *correlation(psar1)* option, which considers panel-specific autocorrelation.

Accuracy metrics evaluate the performance of a model by comparing the observed with predicted values. Three accuracy metrics widely used were selected [200,254]. These are the mean absolute error (MAE), the root mean square error (RMSE) and the coefficient of determination (R^2).

MAE is most commonly used and easiest to interpret directly, representing the average of the absolute errors [118,158,170,255,256]. RMSE [68,161,168,170,170,257] is also very common and it exaggerate the presence of outliers. Both accuracy metrics depend on the scaling of the variables, which may be inconvenient if the criteria are used for comparing predicting accuracy across different variables [258]. Both MAE and RMSE avoid the negative values to cancel the positive ones and both have the same units as the quantified plotted.

The accuracy metrics MAE and RMSE can be calculated using Eq. 4.3 and Eq. 4.4, respectively.

$$MAE = \frac{\sum_{i=1}^{n} \left\| y_{observed} - y_{predicted} \right\|}{n} \quad i = 1,2,\dots n \; [ºC] \qquad \text{Eq. 4.3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left[y_{observed} - y_{predicted} \right]^2}{n}} \quad i = 1,2,\dots n \; [ºC] \qquad \text{Eq. 4.4}$$

where, $y_{observed}$ is the observed values and $y_{predicted}$ is the predicted values and *n* stands for the total number of observations.

The coefficient of determination (R^2), which is a default outcome of the statistical analysis performed in STATA11 software, was also used and provides information about the goodness of fit of a model. R^2 is a figure between 0 and 1, is a measure of effect size and it represents the proportion of the variation in the dependent variable that is attributable to the explanatory variables [116].

The higher the R^2 and the smaller the error values are, the better the model is to predict the actual measurements [68].

4.3.2 Description of database used in statistical models

The independent variables considered for the statistical analysis are classified in three primary groups: a) climatic conditions, captured through the outdoor temperatures; b) socio-economic factors, aiming to depict household characteristics; and c) building characteristics, reflecting the physical characteristics of the dwelling and heating systems.

In order to capture the complexities inherent within the residential building stock, a database that contains as much information as possible on the three groups is needed [68].

The socio-economic factors and building characteristics dataset was gathered through the survey (see section 4.1.3). These variables and its categories are listed in Table 8. The outdoor temperatures resulted from the undertaken monitoring campaign (section 4.1.2). The daily mean outdoor temperatures dataset considered a range of values from 1 to 14ºC for the three different predicting models.

Before applying the linear regression with panel-corrected standard errors, an initial screening was conducted to assess the potential impact of each variable in the indoor temperature. The screening involved two main steps. The first concerned the analysis of the sample size for each variable collected through the surveys. The second step was the assessment of multicolinearity among the subset of variables selected from the first step.

In the first criterion, it was established that the size of each variable (N) should be greater than 70, which guarantees that approximately 50% of the responses for each variable are available. This implied the exclusion of the following variables: total area; bedroom and living room´s area; and roof insulation. In the second step, multicolinearity was analysed using correlation coefficients. The correlations between nominal variables (and between nominal and ordinal variables) were checked using the Cramer´s V coefficient, and the correlations between ordinal variables were verified using the Spearman correlation coefficient.

Table B.10, in Appendix B, presents the correlation coefficients between all variables. In this step, it was decided to exclude from the analysis variables with correlation coefficients higher than 0.6 in order to avoid problems with the estimations.

Table 18 presents the final set of independent variables that constitute the database used in the statistical models and also the type of variables.

Table 18. Set of independent variables included in the prediction models.

Variable name	Type of variable	Bedroom	Living room
Household	Nominal	X	
Household size	Ordinal	X	
Monthly net income	Ordinal		X
Professional situation	Nominal	X	
Value comfort (bed./liv.)	Binary	X	X
Apart/house	Nominal	X	X
Age construction	Ordinal	X	X
Wall insulation	Ordinal		X
Wall thickness	Ordinal	X	
Window frame	Nominal	X	X
Window orientation (bed./liv.)	Nominal	X	X
Type equipment (bed./liv.)	Nominal	X	X
Tout	Continuous	X	X

4.4 Results and discussion

The results obtained for the three predicting models developed are reported in Table 19. In particular, Table 19 reports the estimates from the linear regression with panel-corrected standard errors (i.e., the coefficients, standard errors, and *p*-values), the number of observations included in each model, the coefficient of determination (R^2), the significance (Sig.), and the accuracy metrics MAE and RMSE (see section 4.3.1).

The prediction models were found to be statistically significant (χ^2 test with *p*-value < 0.0001). The model for the bedrooms explains 89% of the variability of indoor temperatures in the occupied period. The models for the living rooms in the occupied and in the 24h period explain 91% and 90% of the variability of indoor temperatures, respectively.

These values are within the range of results found in Kelly *et al*. [68] who achieved R^2 values between 0.45 and 0.88 when applying linear regression with panel-corrected standard errors. In addition, when analyzing the accuracy of the models it can be observed that models present relatively low errors. In particular, MAE is approximately 1ºC for all the models, and RMSE varies between 1.3 to 1.6ºC, depending on the model.

Also, in order to explore the face validity of the panel regression results, a standard linear regression was estimated. The results obtained are in line with panel regression results. In particular, the values of R^2 were 0.82, 0.78 and 0.80 for bedrooms in the occupied period, and living rooms in the occupied and 24h period, respectively. Nevertheless, the results of the panel regression (see R^2 values in Table 19) are more accurate, indicating that it is a better option for modeling indoor temperatures.

From Table 19 it is possible to conclude that socio-economic factors and building characteristics, as well as climatic conditions affect significantly the bedroom and living rooms indoor temperatures.

It is worth mentioning that approximately 73% of the variability presented in bedroom temperatures in the occupied period is explained by the building characteristics (i.e., age of construction; apartment/house; wall insulation; window frame; window orientation and type of equipment). Socio-economic factors (i.e., type of household; no. of households; comfort value and professional situation of the active households) are able to explain 14% of the bedroom temperatures in the occupied period, whereas the outdoor temperatures only explain 3%.

In addition, approximately 85% of the variability of living room temperatures for the occupied period, are explained by the building characteristics (i.e., age of construction; apartment/house; wall thickness; window frame; window orientation and type of equipment), 4% by the socio-economic factors (i.e., type of household; no. of households; comfort value and monthly net income) and 1% are explained by the outdoor temperatures. Similarly, the indoor living room temperatures in the 24h period are mainly explained by building characteristics (81%) and socio-economic factors (7%), followed by outdoor temperatures (2%). These results are in line with several studies that highlight the importance of the building characteristics as one of the main factors influencing indoor temperatures [12,16,19,117,259].

Table 19. Results of the linear regression with panel-corrected standard errors models.

Variable name	Bedroom occupied period			Living room occupied period			Living room 24h period		
	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value
Tout	0.0896	0.01666	*0.000*	0.137	0.01513	*0.000*	0.125	0.02021	*0.000*
Age of construction									
1946-1960	(base)			(base)			-4.598	0.7379	*0.000*
1961-1970	5.326	0.8609	*0.000*	9.287	0.6920	*0.000*	4.307	0.5006	*0.000*
1971-1980	1.136	0.3324	*0.001*	3.535	0.9774	*0.000*	-5.071	0.6232	*0.000*
1981-1990	5.098	0.5636	*0.000*	3.997	0.4980	*0.000*	-1.757	0.3665	*0.000*
1991-2000	5.131	0.6367	*0.000*	8.752	0.5967	*0.000*	1.942	0.2781	*0.000*
2001-2011	8.501	0.8187	*0.000*	6.663	0.6758	*0.000*	(base)		
Apart./House									
Apartment	(base)			(base)			(base)		
House	-5.875	0.4108	*0.000*	2.396	0.9691	*0.013*	5.284	1.0460	*0.000*
Wall thickness									
<20 cm				(base)			-3.534	0.3222	*0.000*
20-40 cm				1.630	0.3144	*0.000*	-3.537	0.1992	*0.000*
>40 cm				5.167	0.3963	*0.000*	(base)		
Wall insulation									
None	(base)								
Until 4 cm	2.291	0.2621	*0.000*						
Over 4 cm	3.564	0.6996	*0.000*						
Window frame									
Aluminium	(base)			(base)			(base)		
Wood	3.016	0.5432	*0.000*	-6.806	0.3343	*0.000*	-4.785	0.3177	*0.000*
PVC	2.262	0.4393	*0.000*	-0.663	0.3408	*0.052*	-0.794	0.2641	*0.003*
Window orientation (bed./liv.)									
North	2.236	1.0823	*0.039*	(base)			-3.203	0.3476	*0.000*
East	2.815	0.5663	*0.000*	2.728	0.7274	*0.000*	-0.928	0.4005	*0.021*
South	-2.022	0.3982	*0.000*	-0.563	0.2845	*0.048*	-3.158	0.3474	*0.000*
West	(base)			1.595	0.4274	*0.000*	(base)		
Type equip (bed./liv.)									
No equipment	(base)			-6.376	0.4613	*0.000*	(base)		
Electrical radiador	4.664	0.4100	*0.000*	-3.815	0.8939	*0.000*	5.159	0.5693	*0.000*
Thermoventilator	6.198	0.7039	*0.000*	-1.907	1.1433	*0.095*	6.724	0.9439	*0.000*
Open fireplace	---	---	---	-9.159	0.3863	*0.000*	-2.124	0.3858	*0.000*
Closed fireplace	7.386	0.6051	0.000	-7.701	0.6677	0.000	-3.2763	0.8808	0.000
Ar condicioner	-8.313	0.6024	*0.000*	---	---	---	---	---	---
Gas boiler	-1.227	0.9768	*0.209*	-3.169	0.9519	*0.001*	4.769	0.6553	*0.000*
Diesel boiler	2.073	0.9252	*0.025*	---	---	---	---	---	---
Wood boiler	5.397	0.4160	*0.000*	-5.833	0.7720	*0.000*	-1.742	1.0306	*0.091*
Salamander	3.080	0.7353	*0.000*	(base)			3.427	0.4480	*0.000*

Table 19. Results of the linear regression with panel-corrected standard errors models (continuation).

Variable name	Bedroom occupied period			Living room occupied period			Living room 24h period		
	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value
Household									
Children and adults and older people	(base)			(base)			(base)		
Children and adults	6.515	0.9178	*0.000*	5.794	0.8992	*0.000*	8.332	0.9200	*0.000*
Adults	8.127	0.8193	*0.000*	4.055	1.0988	*0.000*	7.551	1.0826	*0.000*
Adults and older people	11.681	1.4674	*0.000*	9.117	1.1087	*0.000*	10.614	1.0596	*0.000*
Household size									
0-2	(base)								
3-4	2.190	0.5332	*0.000*	(base)			(base)		
5-6	8.846	0.7153	*0.000*	-2.405	0.2833	*0.000*	-1.579	0.2727	*0.000*
7-8	5.923	1.0097	*0.000*	2.509	0.7386	*0.001*	0.926	0.8149	*0.256*
Comfort value (bed./liv.)									
No value	(base)			(base)			(base)		
Value	-2.652	0.4057	*0.000*	3.168	0.4952	*0.000*	0.687	0.5041	*0.173*
Profess. Situation									
Half employed	5.790	1.0357	*0.000*						
No active households	11.799	1.5589	*0.000*						
All unemployed	6.033	0.9501	*0.000*						
All employed	5.411	1.0766	*0.000*						
Mostly unemployed	(base)		*0.000*						
Monthly net income									
351-750 €/month				(base)			(base)		
751-1250 €/month				3.465	0.4445	*0.000*	1.477	0.3838	*0.000*
1251-2000 €/month				4.345	0.6100	*0.000*	5.565	0.5963	*0.000*
2001-3000 €/month				4.748	0.6315	*0.000*	5.133	0.6327	*0.000*
3001-5000 €/month				5.843	0.6879	*0.000*	5.290	0.6583	*0.000*
Const	-6.285	1.9628	*0.001*	-0.148	1.488	*0.921*	4.746	1.0981	*0.000*
R^2	**0.892**			**0.910**			**0.897**		
Sig.	**0.000**			**0.000**			**0.000**		
No. observations	**3630** (41 dwellings)			**3321** (37 dwellings)			**3322** (37 dwellings)		
MAE (ºC)	**1.12**			**1.02**			**0.99**		
RMSE (ºC)	**1.51**			**1.55**			**1.30**		

In order to provide a sensitivity analysis on the accuracy of the models to predict indoor temperatures, a comparison between the observed and the predicted values was carried out for one (randomly selected) of the 141 dwellings. Figure 23, Figure 24 and Figure 25 show three plots that exhibit how the predicted daily mean indoor temperatures compare against the observed readings for bedroom and living room at occupied period and living room for the 24h period, respectively.

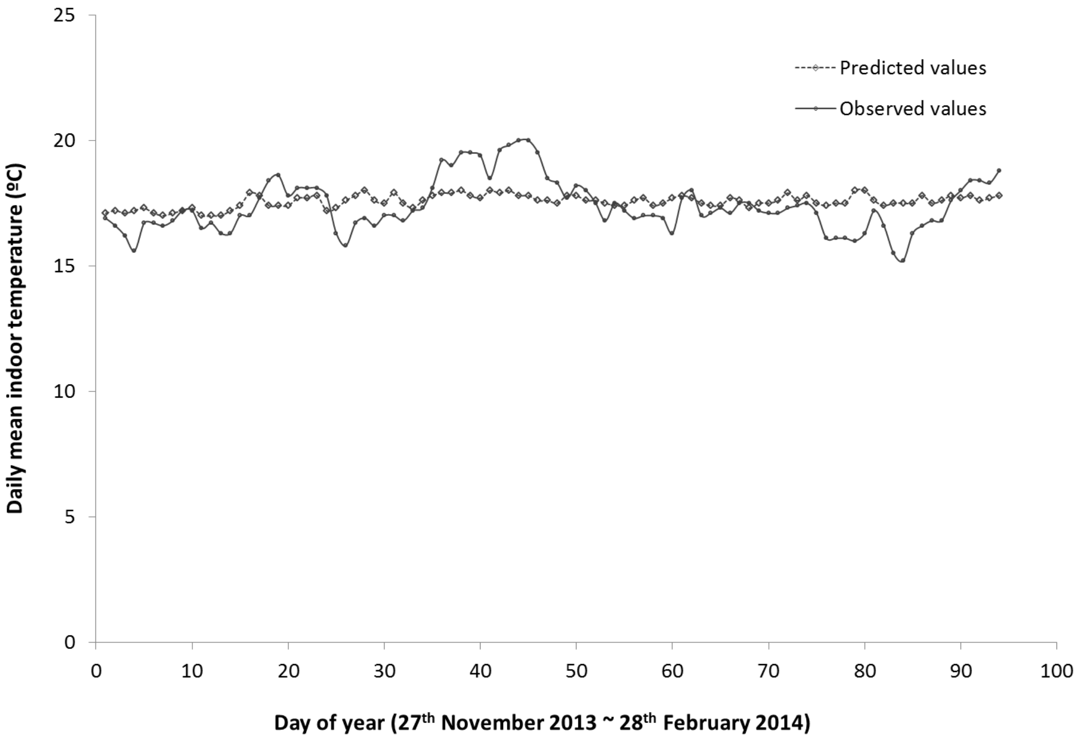

Figure 23. Predicted and observed daily mean indoor bedroom temperature for one dwelling for the occupied period.

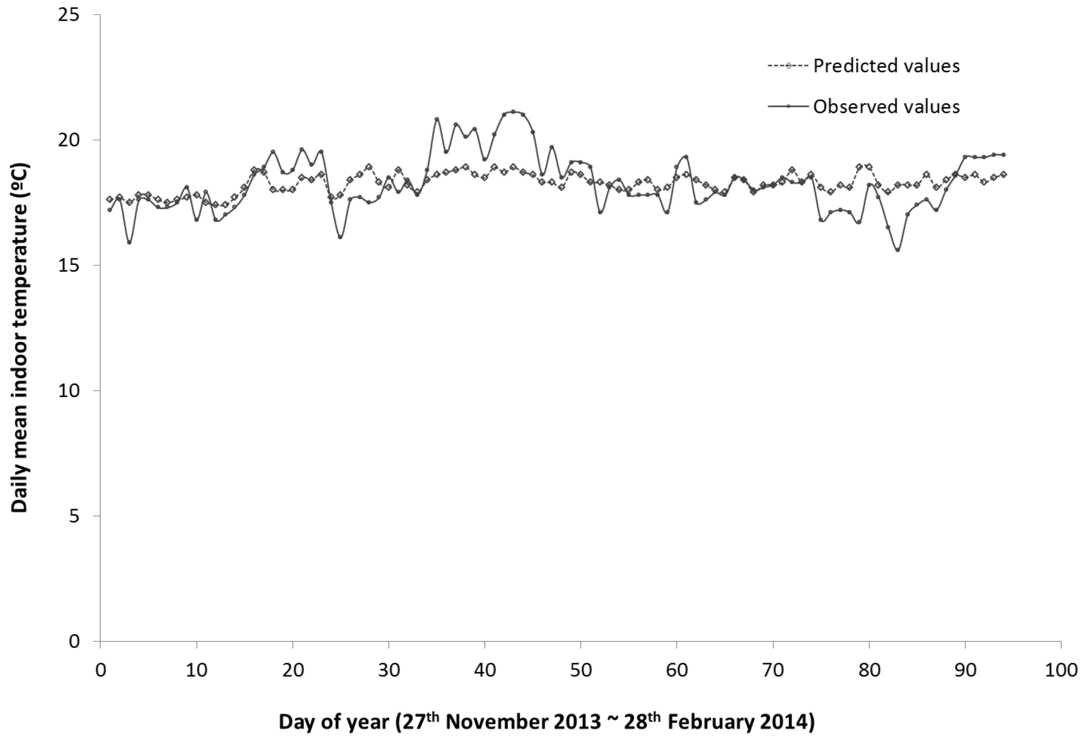

Figure 24. Predicted and observed daily mean indoor living room temperature for one dwelling for the occupied period.

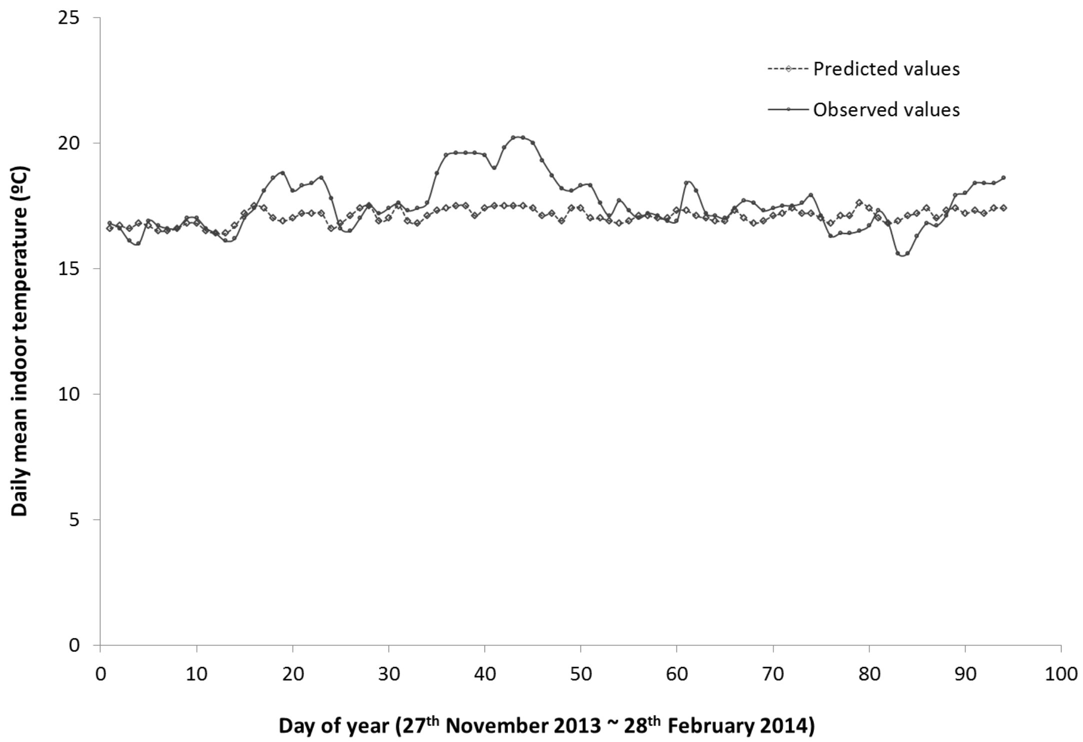

Figure 25. Predicted and observed daily mean indoor living room temperature for one dwelling for the 24h period.

For this dwelling, all the three distributions of the predicted values match reasonably the distribution of the observed values. There are significant deviations for the minima temperatures (e.g., between 14^{th} and 24^{th} of February) and for the maxima temperatures (e.g., between 28^{th} December and 17^{th} January). This may derive from the fact that the prediction models do not account for variables capturing heating patterns, such as the length of heating in the winter season and the length of heating during the day.

4.5 Conclusions

This chapter characterized the actual indoor temperatures and heating patterns in the residential buildings in Northern Portugal during the winter season. In addition, it also developed models to predict actual indoor temperatures, identifying its main determinants in the residential buildings in Northern Portugal.

From the empirical analysis aiming to characterize indoor temperatures, it was possible to draw several conclusions.

Besides occupant´s effort on resorting to thermal adaptation strategies (e.g., blankets and hot drinks), some (68%) pointed out their preference for warmer temperatures.

The observed daily mean indoor temperatures were 15ºC for the bedrooms and 16ºC for the living rooms, which are much lower than the reference values of 18ºC assumed in the current Portuguese regulation of the thermal performance of the residential buildings [73]. If considering only the occupied period, the observed daily mean indoor temperatures are slightly higher than those during the 24h period, particularly 15ºC for the bedrooms and 17ºC for the living rooms. Still, a wide variation in temperatures among and within locations was observed, with records of daily mean temperatures in the occupied period as low as 10ºC in sleeping rooms and in living rooms.

The results also indicated that indoor temperatures are significantly below the levels putatively recommended. In addition, although using a general adaptive comfort model that can only be considered for indicative purposes, the results show that indoor conditions are far from being entirely equal to the adaptive comfort patterns, which would require about 15.3ºC to 19.0ºC indoors, depending on location and month. The verification of what might be considered, in some cases, cold indoor temperatures, could be an indication of suppressed thermal comfort conditions, which goes in line with the possible existence of an energy use gap for heating in the residential building stock (see section 1.2).

Further interesting conclusions were withdrawn from the obtained results, as follows:

- It was found that lower outdoor temperatures do not necessarily imply lower indoor temperatures. For instance, Bragança has outdoor temperatures lower than Porto but presents similar indoor temperatures. Thus, outdoor temperature is not the only factor influencing the indoor temperature, as it could be confirmed from the regression results;
- Two main typical indoor temperature profiles over time were identified. One relates to fairly higher constant temperatures, with few oscillations over time; and the other concerns higher temperature´s amplitude and more prone to the outdoors´ influences. The latter might be a consequence of less heating practices, lower performance of building fabrics or heating systems;
- It was verified that bedrooms were usually heated before sleeping hours, with peak bedroom temperature found to occur in the evening (around 11:00). The peak living room temperature is usually reached in the evening, when the room is mostly occupied.

In addition, the models developed using linear regression with panel corrected standard errors revealed to be very promising at predicting the daily mean bedroom temperature in the occupied period (R^2 = 0.89), and the living room temperatures in the occupied and 24h period (R^2 = 0.91 and 0.90, respectively). The results showed that climatic conditions, and especially socio-economic factors and building characteristics, affect significantly the bedroom and living rooms indoor temperatures. Moreover, it could be concluded that the variability presented in mean indoor temperatures modelled are mainly explained by building characteristics (ranging from 73%-85%), followed by socio-economic factors (varying from 4%-14%), and outdoor temperatures (1% to 3%).

CHAPTER 5

MODELING HEATING ENERGY USE IN RESIDENTIAL BUILDINGS

The energy needs for heating a dwelling depend crucially on the physical characteristics of the building, on the climate where it is located and on the occupant's behaviours, with emphasis to the magnitude, space and time distribution of the temperatures required. The physical characteristics of the building are something that is by nature well-defined. Furthermore, they only change in time when there are upgrades to the envelope. Although it may sometimes be difficult to know the details, in the case of existing buildings (e.g., the thickness of thermal insulation hidden inside walls), it is usually possible to make at least a reasonable inference from energy performance certificates (EPC). The climate, despite its inherent variability from year to year, is something that is also reasonably well characterized through databases.

The magnitude, space and time distribution of the temperatures required are however a much volatile aspect, which depends on the occupants preferences and/or capacity to afford the heating. While 'reference' patterns are assumed for computing the energy needs, e.g., for energy labeling and certification purposes, it is known that in practice they may differ very much from those assumed [20]. For example, results from chapter 4 revealed that bedroom and living temperatures were much lower than the reference values of 18ºC assumed in the current Portuguese regulation of the thermal performance of the residential buildings [73]. This often leads to undervaluing (or even discrediting) the information from the assessments and/or energy performance certificates (EPC). However, given that those assessments do contain a reasonable or often a good description of the building physical characteristics and of the climate, a much more and better use of the information could be extracted if a relationship between the reference energy demand, indoor temperature, and the heating energy use was known. For example, given the reference energy demand and a certain indoor temperature intended, it would be possible to estimate the heating required; Or, given the maximum amount of heating than can be afforded, it would be possible to estimate the resultant indoor temperatures.

There is a constant search for user-friendly models to predict heating energy use in the residential buildings with a greater degree of freedom in terms of assumptions for the occupant behaviour (i.e., operating conditions) [63]. Furthermore, databases, such as the EPBD-derived EPC databases, are very attractive tools to estimate heating energy use (and indoor temperatures) as they hold an extensive number of certificates already issued with important information on building data (e.g., theoretical heating energy demand under reference conditions (HDRC)). Provided that there is an understanding of the relationship between the *heating energy use*, occupant behavior (e.g. *indoor temperatures*) and *HDRC,* and using the HDRC values from EPC databases, it is possible to estimate heating energy use or indoor temperatures values for different levels of occupant behaviour.

Dynamic modeling of individual dwellings can estimate accurately the heating energy use, but it is complex and time-consuming. This chapter explores the use of statistical models coupled with simulations and calculation data to predict heating energy use or indoor temperatures. The models are applicable to residential buildings in any geographical context and in the Portuguese context. In addition, this chapter proposes the use of the models developed to assess the 'heating gap' of the residential building stock in Portugal mainland (once the estimated 'reference heating gap' value, in chapter 3, was based on stringent thermal comfort values).

The developed models in this chapter are useful tools for policy formation [260] and an important contribution to the modeling and planning of countries' whole energy systems.

The structure of this chapter is the following. Section 5.1 gives a brief contextualization of the modeling concept and section 5.2 describes the architecture of the developed models. Section 5.3 describes the databases used in the statistical models. Section 5.4 presents the statistical models adopted. Section 5.5 presents the models developed with values of HDRC that come directly from building simulation with ESP-r, and therefore in principle can be used for any geographical context – hence the label 'universal'. Section 5.6 uses values of HDRC computed according to the methodology of the Portuguese energy certification system, and therefore are labelled as 'Portugal-specific'. Section 5.7 presents the graphical representation of the energy-temperature relationship, whereas section 5.8 exhibits the assessment of the 'heating gap'. Section 5.9 presents the main conclusions of the study developed under this chapter.

5.1 Modeling concept

Each certificate, representing a specific building, issued in energy rating/certifications schemes´ databases, can provide HDRC values. In chapter 3, the HDRC served as 'majorant value' for theoretical heating energy demand (THD) under thermal comfort conditions, but aligned with a stringent perspective of thermal comfort (*(3)* in Figure 1, section 1.2) to support the preliminary assessment of the 'reference heating gap' of the residential building stock.

In the Portuguese case, the HDRC values are calculated as 'useful' energy values. The HDRC, of a particular building, is dependent on several factors, such as physical characteristics of the building archetype (M); geographical location of the building (L); reference heating pattern ($HPat_{ref}$); reference indoor heat gains (HG_{ref}) and reference set point temperature (Tsp_{ref}). This relationship can be expressed, in general, by Eq. 5.1 as follows:

$$HDRC = f(M, L, HPat_{ref,} HG_{ref}, Tsp_{ref}) \quad [kWh/m^2.year] \qquad \text{Eq. 5.1}$$

The heating energy use (HEU) of a particular building, which is also calculated as 'useful' energy, depends on the building characteristics, climate conditions, and occupant´s heating behaviour [12,17,29,54,63,117,261–264]. More precisely on: geographical location of the building (L); physical characteristics of the building archetype (M); heating pattern (HPat); indoor heat gains (HG) and set point temperature (Tsp). The latter three are defined by the occupant´s behaviour.

The heating energy use can be therefore expressed, in a simple manner, by the relationship described in Eq. 5.2.

$$HEU = f(M, L, HPat, HG, Tsp) \qquad [kWh/m^2.year] \qquad \text{Eq. 5.2}$$

It is possible to create a more operational and simpler version of the model (E.q. 5.2) replacing the building archetype (M), the geographical location (L), the heating patterns (HPat) and indoor heat gains (HG) variables by the theoretical heating energy demand under reference heating conditions (HDRC). Besides all the limitations behind the methodology used to estimate HDRC (derived mainly from assumptions, see section 1.2), the convenience of using the HDRC as a *proxy* variable lies on the fact that, in principle, this information can be directly gathered from any energy rating/certification´s databases. Other major benefit of using HDRC is that it overcomes the difficulty of getting access to detailed data at building level.

The form intended for the model proposed is represented in Eq. 5.3 and describes the HEU as a function of HDRC and Tsp. The model generates results in terms of useful or 'net' energy.

$$HEU = f(HDRC, Tsp) \qquad [kWh/m^2.year] \qquad \text{Eq. 5.3}$$

Based on Eq. 5.3, it is also possible to model the Tsp as a function of HEU and HDRC. This relationship is expressed in the form of Eq. 5.4 and provides information regarding the minimal guaranteed indoor temperature in spaces when heated that corresponds to a specific combination of HEU and reference HDRC:

$$Tsp = f(HDRC, HEU) \qquad [kWh/m^2.year] \qquad \text{Eq. 5.4}$$

With the specifications above, the HDRC is considered a key variable for modeling the heating energy use (HEU) or the indoor temperature, named here as set point temperature (Tsp). In this study, the modeling of HEU or Tsp was obtained using HDRC reflecting three different contexts:

1) a standard reference conditions dataset ($HDRC_{st}$) derived from thermal building simulations. The temperature profiles and heating patterns were based on the RCCTE regulation´s [72] reference heating conditions. RCCTE regulation is the former

transposition of EPBD [6] for residential buildings. This analysis aims to create models that can be applicable to different geographical contexts;

2) RCCTE reference conditions dataset ($HDRC_{RCCTE}$) derived from the RCCTE regulation´s energy calculation model [72];
3) REH reference conditions dataset ($HDRC_{REH}$) derived from the REH regulation´s energy calculation model [73]. REH regulation is the current transposition of the recast EPBD [7] for residential buildings.

The two later analyses intend to develop models specifically tailored to the Portuguese context (called Portugal specific models: the RCCTE specific models and the REH specific models). Although the former RCCTE regulation is no longer in place, there are currently several certificates issued that were derived from this regulation.

In summary, firstly, it was developed HEU or Tsp universal prediction models considering theoretical heating energy demand under standard reference conditions ($HDRC_{st}$). Secondly, it was developed HEU or Tsp prediction models that are Portugal specific, considering theoretical heating energy demand under RCCTE and REH reference conditions ($HDRC_{RCCTE}$ and $HDRC_{REH}$).

5.2 Modeling architecture

The development of the models implied the construction of a variable database to be used in the statistical models. In order to characterize the relationships explained by Eq. 5.3 and 5.4, the database needed to be composed at least by three different variable datasets that will support the models: HEU, Tsp and HDRC datasets. Figure 26 schematizes the origin of the three datasets that compose the database used in the statistical models.

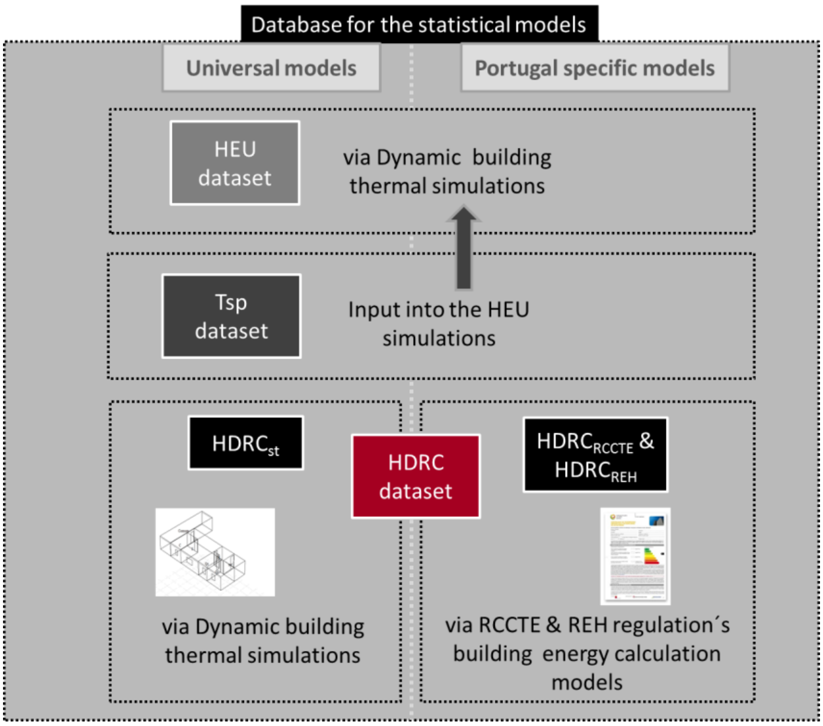

Figure 26. Schematic illustration of the construction of the database used in the statistical models.

For both universal and Portugal specific models, the HEU dataset resulted from dynamic building thermal simulations and the Tsp dataset is an input to those HEU simulations. The only difference between the universal and the Portugal specific models is that, in the first, the HDRC dataset ($HDRC_{st}$) resulted from dynamic building thermal simulations, whereas in the second, the HDRC variable dataset, i.e. the $HDRC_{RCCTE}$ and $HDRC_{REH}$, resulted from the RCCTE and REH regulation's building energy calculation models, respectively.

All the dynamic thermal building simulations were run with the building energy model ESP-r. ESP-r is a well proven and validated tool that has been used in several research studies in the context of thermal buildings field [34,265,266].

The database used in the statistical models was therefore composed by inputs to and outputs from simulations and calculations methods.

Figure 27 explains in more detail the methodology behind the construction of the database to model HEU or Tsp. The Tsp, HEU and HDRC datasets are highlighted in red.

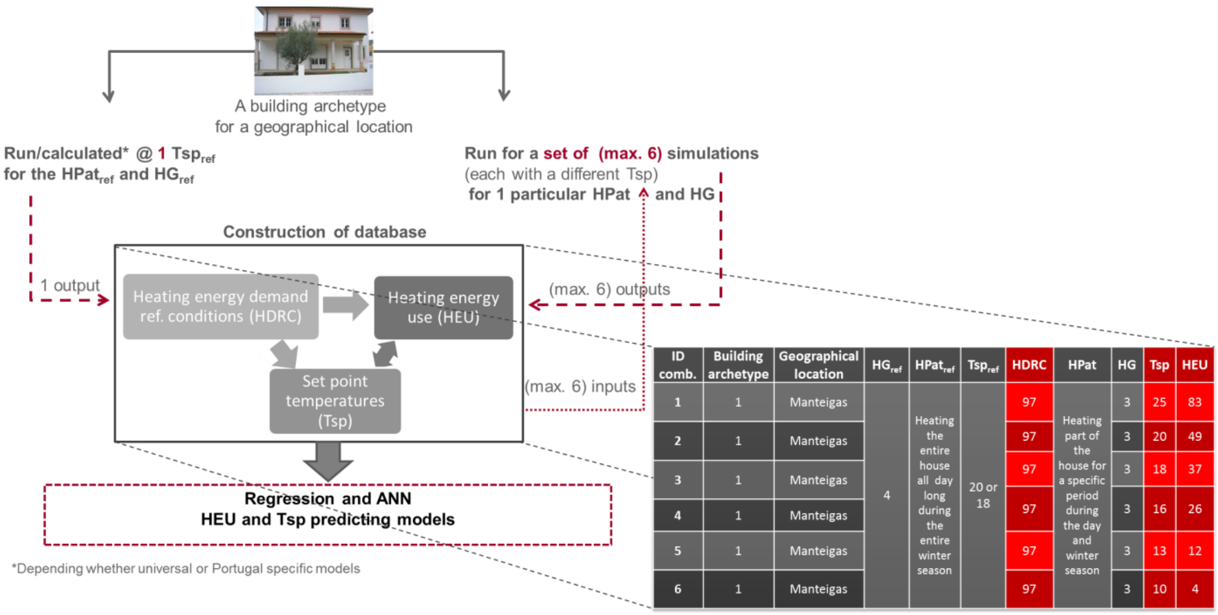

Figure 27. An outline of the methodology proposed for the development of models.

Recalling Eq. 5.2, HEU varies with building archetype (M), geographical location (L), heating patterns (HPat), indoor heat gains (HG) and set point temperature (Tsp). In particular, for each combination of a building archetype and geographical location (e.g. Manteigas), considering a specific heating pattern (e.g. heating 20m^2 of the house for 4 hours per day during the winter season) and indoor heat gains (e.g. 3 W/m^2), simulations were run for a number (*maximum of 6*) of different specific values of Tsp (e.g., from 10ºC to 25ºC). The construction of the HEU dataset was therefore built upon various combinations of M, L, HPat and HG, where each takes at a maximum of 6 different Tsp values, resulting each in a different HEU output values. The Tsp dataset corresponds to input values in HEU simulations.

Considering Eq. 5.1, HDRC varies with building archetype (M) and geographical location (L), but with reference heating patterns ($Hpat_{ref}$), indoor heat gains (HG_{ref}) and set point temperature (Tsp_{ref}). The same combinations of building archetypes and geographical locations (e.g., Manteigas), used in the construction of the HEU dataset, were run in simulations or calculated considering the reference set point temperature (20ºC or 18ºC, depending on the

HDRC variant), the reference heating pattern (heating the house all day long during the entire winter season) and the reference indoor heat gains (4 W/m^2). Thus, the construction of HDRC dataset was built upon several combinations of M, L, $HPat_{ref}$, HG_{ref} and Tsp_{ref}, resulting each in a single HDRC output value.

At the end, the HEU, HDRC and the Tsp datasets built up the database used in the regression and artificial neural networks (ANN) models applied for modeling HEU or Tsp. The HEU was modeled as a function of the independent variables HDRC and Tsp, whereas the Tsp was modeled as a function of the independent variables HDRC and HEU.

As mentioned previously, the HEU dataset resulted from building thermal simulations and the HDRC dataset was obtained either from building thermal simulations (in case of universal models) or building energy calculation models (in case of Portugal specific models). Various building models considered in ESP-r simulations and energy calculation models were required to create the database to be used in the statistical models. The building models implied the need for several combinations of the categories: building archetypes, geographical locations, heating patterns, set point temperatures and indoor heat gains. The range of values of those categories and the combination between them were selected to be the widest and diverse as possible to capture a vast range of HEU, $HDRC_{st}$, $HDRC_{RCCTE}$ and the $HDRC_{REH}$ output values. I.e., so that HEU or indoor temperature predicting models would perform estimations for a wide range of each independent variable/representativeness [69]. Next sections present the possibilities considered within these categories.

5.2.1 Building archetype

Different building archetypes (M) were constructed in ESP-r for the HEU simulations. The selected values for physical characteristics and surroundings of building archetypes are defined in Table 20.

Table 20. Physical characteristics and surroundings of the building archetypes (M).

Characteristics	Discrete values	
Type of dwelling	Detached house; semi-detached house; terrace house; apartments	
	For houses	*For apartments*
Construction period	<1960; 1961-90; 2006-14	
Air infiltration rate/natural ventilation (IR) (ac/h)	0.6; 0.8; 1.0; 1.2; 1.5; 1.7	0.6; 1.0; 1.2; 1.5; 1.7
Floor area (m^2)	150^{I}; 225^{II}; 251^{I}; 300^{III}; 350^{I}	100^{IV}; 141^{IV}; 181^{IV}; 200^{I}
% of glazing area per facade [190]	10%; 43%; 75%	
Orientation of the facades	All orientations	West; North; South
No. of floors	2; 3; 4	1;2
Overhang	None; Overhang of 1.5m just 1st floor; Overhang of 1.5 m on both floors	None; Overhang of 1.5m; Overhang of 0.5 m
Type of urbanization	No buildings in the surroundings; Houses in the surroundings with same height; Other type of houses in the surroundings	No buildings in the surroundings; Apartments in the surroundings

^{I} Resultant from 2 floors;
^{II} Resultant from 3 floors;
^{III} Resultant from 4 floors;
^{IV} Resultant from 1 floor.

The *type of dwelling* was composed by six categories: three representing houses (detached house, semi-detached house and terrace house), and the other three, apartments located between other apartments with 1, 2 or 3 external facades (1F, 2F, 3F, respectively).

Three values of *percentage of glazing area in each facade* were considered for both type of buildings: 10%; 43% and 75%.

The *construction period* was categorized in three 'slices': <1960; 1961-1990 and 2006-2014. Each slice was characterized by different combinations of building´s construction and materials and air infiltration rates. Details of building´s construction and materials for the three construction periods are presented in Table C.1 and Table C.2, in Appendix C, for houses and apartments, respectively.

In terms of *number of floors,* houses were designed for 2, 3 and 4 floors, whereas apartments considered 1 and 2 floors. The *floor area* values corresponded to 150, 250, 350m^2, for houses with 2 floors and 225m^2 and 300m^2 for houses with 3 and 4 floors, respectively. For the apartments, often smaller in size, the *floor area* values corresponded to 100, 140, 180m^2 for apartments with 1 floor and 200m^2 with 2 floors. These values were defined based on data provided by the National Institute of Statistics (INE) database [214].

In terms of the *orientation of facades*, it was considered that facades had four possible orientations (i.e., South, North, West and East) for the houses, whilst facades of the apartments had three possible orientations (South, West, or North).

Regarding the presence of an *overhang* that could provide shading to the windows, houses were simulated using three options: a) no overhang (i.e., no shading); b) overhang of 1.5 m length in the first floor; c) overhang of 1.5 m length in the two floors. In turn the apartments were simulated with: a) no overhang; b) overhang of 1.5 m length, and c) 0.5 m length.

The *type of urbanization* recreates different scenarios of shading and infiltration rates. For the houses, the variable *type of urbanization* was created by running simulations with: a) no buildings in the surroundings; b) house is surrounded mainly by other houses with the same height; and c) house is surrounded by houses and apartment buildings. In turn, the type of urbanization for the apartments was captured by running simulations with: a) no buildings in the surroundings; and b) with apartments in the surroundings.

The *air infiltration rate/natural ventilation*[8] (IR) is influenced by several factors, namely the construction period, the type of urbanization, the type of window´s insulation (e.g. in accordance with the construction period; well insulated; and very well insulated), and the window opening behaviour (e.g. normal patterns; excess in opening windows).

[8] ESP-r does not allow the direct input of the natural ventilation values, therefore, they were considered along with air infiltration rates.

In reality air infiltration rates/natural ventilation, depending on the situation, can vary with time and space. For simplicity, HEU simulations assumed a constant IR values (between 0.6 to 1.7ach/h) for everyday of the week[9] and every rooms.

In terms of window's control, it was assumed that buildings receive sunlight through windows every day during daytime. Consequently, the thermal conductivity coefficient values of windows were estimated as a weighted value, considering that for half of the time the venetians are open. Also, complex fenestration construction (CFC) files, for each type of window, were implemented in ESP-r using the Glazing Shading Layer Editor (GLSedit) tool. This tool contains an extensive glazing product selection for many manufacturers and was designed for quick synthesis of a glazing product with or without shading components. The output information on optical proprieties of the CFC can then be read by ESP-r [267]. Normal solar, visible and longwave optical proprieties for glazing and venetian blinds layers assumed from the GSLedit´s database, for the three construction periods and for both houses and apartments, are presented in Table C.3, in Appendix C.

In addition, thermal conductivity coefficient values were accounted for thermal bridges for each building archetypes. These were considered by including an equivalent thermal conductivity coefficient U_{eq} for each external facade. The U_{eq} was estimated accordingly to the physical characteristics of each building archetype, using the Eq. 5.5:

$$U_{eq(i)}= \frac{A_{real} \times U_{real} + A_{ftb} \times U_{ftb} + \sum (L_{ltb} \times \Psi_{ltb})}{A_{total(i)}} \quad [W/m^2.ºC] \qquad \text{Eq. 5.5}$$

where, $U_{eq(i)}$ is the equivalent thermal conductivity coefficient (W/m^2.ºC) of facade i; A_{real} is the area of the construction building material in facade i (m^2); U_{real} is the thermal conductivity coefficient (W/m^2.ºC) of the construction building material in facade i (W/m^2.ºC); A_{ftb} is the area

[9]Simulations in EPS-r works primarily with weekly air infiltration rate/natural ventilation inputs that are reproduced for all the year.

correspondent to the beams and pillars (flat thermal bridges) in facade *i* (m^2); U_{ftb} is the thermal conductivity coefficient ($W/m^2.ºC$) of the beams and pillars (flat thermal bridges) in facade *i*; L_{ltb} is the length of the linear thermal bridges (m) in facade *i*; Ψ_{ltb} is the linear thermal transmittance coefficient of linear thermal bridges (W/m.ºC) in facade *i*; $A_{total(i)}$ is the total area (m^2) of facade *i*, excepting the doors and windows.

The values for linear thermal transmittance coefficients were considered from the 2006 RCCTE´s regulation documentation [72]. Table C.4 and Table C.5 in Appendix C, present the estimated values of thermal conductivity coefficient ($U_{eq.}$) for external facades for houses and apartments, respectively.

44 combinations of the physical characteristics and surroundings of the building archetypes were performed and resulted in 44 different building archetypes, which are specified in Table 21.

Table 21. Combinations of physical characteristics of the building archetypes.

No	Type of building	Age	Floor area (m^2)	Orientation of the facades	% of glazing area				Overhang	No. of floors	Type of urbanization	Air infiltration rate/natural ventilation (ac/h)
					N	S	E	W				
1	Detached	06-14	150	All*	10	10	10	10	None	2	No buildings in the surroundings	0.8
2	Terrace	06-14	150	North / South	10	10	0	0	None	2		0.8
3	Semidetached	06-14	150	North / South / West	10	10	0	10	None	2		0.8
4	Apartment (1F)	06-14	100	West	0	0	0	10	None	1		0.6
5	Apartment (3F)	06-14	100	North /South / West	10	10	0	10	None	1		0.6
6	Apartment (2F)	06-14	100	North / South	10	10	0	0	None	1		0.6
7	Detached	<60	150	All*	10	10	10	10	None	2		1.7
8	Detached	60-90	150	All*	10	10	10	10	None	2		1.2
9	Apartment (1F)	<60	100	West	0	0	0	10	None	1		1.5
10	Apartment (1F)	60-90	100	West	0	0	0	10	None	1		1.0
11	Detached	06-14	350	All*	10	10	10	10	None	2		0.8
12	Detached	06-14	251	All*	10	10	10	10	None	2		0.8
13	Apartment (1F)	06-14	181	West	0	0	0	10	None	1		0.6
14	Apartment (1F)	06-14	141	West	0	0	0	10	None	1		0.6
15	Detached	<60	150	All**	10	10	10	10	None	2		1.7

*Building is positioned such that the facades with higher external area are oriented to East and West.

**Building is positioned such that the facades with higher external area are oriented to North and South.

Table 21. Combinations of physical characteristics of the building archetypes (continuation).

No	Type of building	Age	Floor area (m^2)	Orientation of the facades	% of glazing area				Overhang	No. of floors	Type of urbanization	Air infiltration rate/natural ventilation (ac/h)
					N	S	E	W				
16	Apartment (1F)	<60	100	North	10	0	0	10	None	1	No buildings in the surroundings	1.5
17	Apartment (1F)	<60	100	South	0	10	0	0	None	1		1.5
18	Detached	<60	225	All**	10	10	10	10	None	3		1.7
19	Detached	<60	300	All**	10	10	10	10	None	4		1.7
20	Apartment (1F)	<60	200	North	10	0	0	0	None	2		1.5
21	Detached	<60	150	All**	75	75	75	75	None	2		1.7
22	Detached	<60	150	All**	43	43	43	43	None	2		1.7
23	Apartment (1F)	<60	100	North	75	0	0	0	None	1		1.5
24	Apartment (1F)	<60	100	North	43	0	0	0	None	1		1.5
25	Detached	<60	150	All*	10	10	10	10	1.5m, 1st floor	2		1.7
26	Detached	<60	150	All*	10	10	10	10	1.5m, both floors	2		1.7
27	Apartment (1F)	<60	100	West	0	0	0	10	1.5m	1		1.5
28	Apartment (1F)	<60	100	West	0	0	0	10	0.5m	1		1.5
29	Detached	<60	150	All**	10	10	10	10	None	2	Houses with same height	1.7
30	Apartment (1F)	<60	100	North	10	0	0	0	None	1	Apartments	1.7
31	Detached	<60	150	All**	10	10	10	10	None	2	Other type of houses	1.7
32	Detached	<60	150	All**	75	75	75	75	None	2	No buildings in the surroundings	0.6
33	Detached	<60	150	All**	75	75	75	75	None	2		1
34	Detached	<60	150	All*	10	10	10	10	1.5m, both floors	2		0.6
35	Detached	06-14	350	All*	10	10	10	10	None	2		0.6
36	Detached	06-14	350	All*	10	10	10	10	None	2		1.7
37	Detached	<60	150	All**	10	10	10	10	None	2		1.2
38	Apartment (1F)	<60	100	North	75	0	0	0	None	1		1.2
39	Detached	<60	150	All**	10	10	10	10	None	2		0.6
40	Apartment (1F)	<60	100	North	10	0	0	0	None	1		0.6
41	Apartment (1F)	06-14	181	West	0	0	0	10	None	1		1.7
42	Detached	<60	150	All**	75	75	75	75	None	2		1.5
43	Detached	<60	150	All**	75	75	75	75	None	2		1.7
44	Apartment (1F)	06-14	181	West	0	0	0	10	None	1		0.6

*Building is positioned such that the facades with higher external area are oriented to East and West.

**Building is positioned such that the facades with higher external area are oriented to North and South.

The 44 building archetypes were also constructed in Esp-r for the $HDRC_{st}$ simulations, except the fact that, in these simulations, the air infiltration rate/natural ventilation assumed a constant reference value (IR_{ref}) of 0.95ac/h, for simplicity.

As stated in section 5.1, the $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations were performed using each building energy calculation model. The building energy calculation models are simplified methods of calculation (e.g. thermal inertia, thermal bridges [268], solar gains), which can differ from those of ESp-r simulations. According to the input information provided, these models assume certain values by default (e.g. air infiltration rate/natural ventilation, glazing solar factor).

Furthermore, The $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations were based on the same 44 building archetypes presented in Table 21, but were performed as experts would perform when building data is not available. This means that, in some cases, different inputs of thermal conductivity coefficients (see Table C.6 and Table C.7, in Appendix C) and optical proprieties of glazing and venetian blinds (see Table C.8 in Appendix C) were assumed from data available in technical reports. These values, along with those used by default in the model, can therefore differ from the values in the HEU and $HDRC_{st}$ simulations.

Figure 28 illustrates examples of ESP-r building archetypes representing a detached house and an apartment (1F).

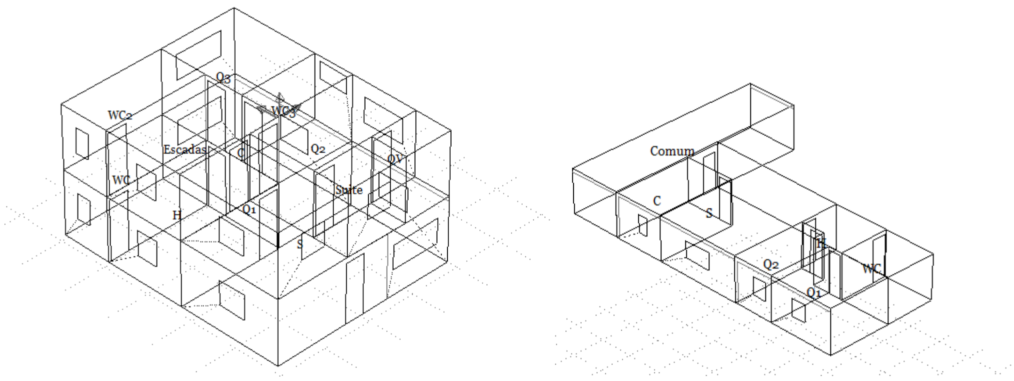

Figure 28. ESP-r Detached house (left). ESP-r Apartment (1F) (right).

5.2.2 Geographical location

Five geographical locations (L) were selected to cover different climates in terms of heating degree days (HDD) (based temperature of 20ºC according to RCCTE regulation [203]), varying between 1060 and 3000: Manteigas (3000), Bragança (2850) Porto (1610), Lisbon (1190) and Faro (1060). Figure 29 indicates the location of the five geographical locations considered in the study.

All these 5 locations were selected to build up the HEU and the three types of HDRC datasets. HEU and $HDRC_{st}$ ESP-r simulations used climate files adapted to match those assumed in the RCCTE [72]/EPC [73].

Figure 29. The location of the five geographical locations considered.

5.2.3 Set point temperature

Set point temperature (Tsp) defines the setting temperature of the heating thermostat in the spaces during the heating period and represents the minimal guaranteed indoor temperature in spaces when heated.

Tsp values could differ depending on space and heating period. For simplicity, each HEU simulation assumed a constant value of Tsp (between 10ºC and 28ºC) to every scheduled rooms during the heating periods, for each day type (weekdays, Saturday and Sunday) of the week[10].

Due to the great amount of daily set point temperature patterns (i.e., hourly distribution of Tsp per each rooms) defined for this work, just an example is illustrated in Figure C.1, in Appendix C, for the case of an apartment 1F with a specific heating pattern (i.e., heated spaces during a specific heating period) and a Tsp value of 20ºC.

The $HDRC_{st}$ simulations assumed a constant value of Tsp_{ref} equal to 20ºC. The $HDRC_{RCCTE}$ calculations used a constant value of 20ºC, whereas the $HDRC_{REH}$ calculations adopted 18ºC.

5.2.4 Heating patterns and indoor heat gains

5.2.4.1 Definition

For simplicity, the heating patterns (HPat) are characterized by the **heating period** (HP) in the winter season and the **percentage of heated area** (HA%). The first is defined as the length of the heating period during the winter season. The latter is defined as the percentage of floor area that is scheduled for space heating in a week[11]. For example, a dwelling with a floor area of

[10] Simulations in EPS-r works primarily with weekly set point temperature inputs that are reproduced for all the year.
[11] Simulations in EPS-r works primarily with weekly inputs that are reproduced for all the year.

100m^2, where 50 m^2 are heated during 12h (out of 24h) in the 7 days of the week, exhibits weekly heated area of 25%.

By definition, the HA% strongly depends on the floor area of the dwelling and on the occupancy and occupants behaviour (OOB) characteristics, in particular: the *heating schedules*, which define the rooms that should be heated and when; the *occupation patterns*, which indicate when and where occupants are at home; and the *number of bedrooms occupied,* which directly affects the heated area; and the *household size,* which indirectly affect the number of rooms that are occupied.

The **indoor heat gains** (HG) are defined by the heat delivered from equipment, lighting and people per square meter. People deliver energy in the form of sensible and latent heat that might vary with time and space. The hourly sensible and latent heat gains from people for a particular room was obtained by attributing a constant metabolic activity and multiplying it by the number of people and the fraction of occupation time in that room for a particular hour. Occupation patterns determining the hourly distribution of people per room were developed. The metabolic activity values are dependent on each person activity at a particular time and place and were assumed from ref. [269].

Lighting delivers energy in the form of sensible heat. The hourly sensible heat gains from lighting for a particular room were obtained by multiplying the power by the fraction of time in that room for a particular hour. Power values were assumed depending on the type of room (e.g., more bulbs for living rooms) and level of energy use (e.g. more or less efficient bulbs). The fraction of time per hour depends mainly on the occupation patterns.

Equipment delivers energy in the form of sensible heat (processes, such as cooking are not considered). The hourly sensible heat gains from equipment for a particular room was obtained by multiplying the equipment power by the fraction of time in that room for a particular hour. Equipment and power were assumed depending on the type of room (e.g., fridges in the kitchens) and level of energy use (e.g. more or less efficient equipment). The fraction of time per hour depends mainly on the occupation patterns.

By definition, the HG depends on the following occupancy and occupant's behaviour (OOB) characteristics, in particular: the *occupation patterns,* for example, dwellings occupied for longer period would result in higher heat gains; the *household size*, for example higher number of people would result in higher heat gains; and the *level of energy,* which defines the lighting and equipment power, for example, higher number of used equipment/bulbs reflect on higher heat gains.

5.2.4.2 Occupancy and occupant´s behaviour characteristics variables to define heating patterns and indoor heat gains

The $HDRC_{st}$ simulations and the $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations took reference values for the heating patterns ($Hpat_{ref}$), as well as for indoor heat gains (HG_{ref}). In particular, it was assumed indoor heat gains (HG_{ref}) of 4 W/m^2, percentage of heated area ($HA\%_{ref}$) of 100%, and entire winter season as the heating period (HP_{ref}).

In contrast to reference heating conditions, the heating patterns and internal heat gains assumed in the HEU simulations were captured from combinations of occupancy and occupant behaviour characteristics (OOB) in order to increase the range of their values.

Table 22 presents the OOB characteristics. Table 22 also indicates which OOB characteristics have an influence on heating patterns and internal heat gains.

Table 22. Occupancy and occupant behaviour characteristics of the heating patterns and indoor heat gains.

OOB characteristics	Discrete values	Heating patterns (HPat) and indoor heat gains (HG)
Heating schedule	When and where occupied (W2); Everywhere, anytime (EA); Everywhere in the occupied period 1 (EO 1) and period 2 (EO 2); Only in common area in the period 1 (CA 1); period 2 (CA 2); and period 3 (CA 3); Specific period (SP)	% of heated area
Occupation patterns	Work time out (WTO); Always at home (ATH); Morning time out (MTO)	% of heated area; Indoor heat gains
No. bedrooms occupied	For houses: 2 and 6 bedrooms occupied; For apartments: 2 and 4 bedrooms occupied	% of heated area
Level of energy use	Low; Normal; High	Indoor heat gains
Household size	2 people; 4 people; 8 people	% of heated area; Indoor heat gains
Heating period	Winter season period; December; January; February; December to January; December to February; November to January; November to February	Heating period

The *number of bedrooms occupied* was different for the houses and apartments. 2 and 6 bedrooms occupied (out of 3 and 6, respectively) were assumed for the houses, whereas for the apartments, 2 and 4 bedrooms were considered occupied (out of 2 and 4, respectively).

The *level of energy use* assumed three *levels*: a) very low energy use, which may result from the use of more efficient equipment/lighting or the reduced number of equipment/bulbs; low energy use; b) high energy use resultant from the use of less efficient equipment/lighting or the abusive use, or high number of equipment/bulbs; c) an intermediate energy use values.

The *heating schedule* aims to capture the main heating schedules that occur in dwellings. It assumed six options as follows: a) the rooms occupied by the households will be heated only during the time of their occupation (W2); b) all the rooms of the dwelling will be heated during the 24h period, regardless the dwelling occupation (EA); c) all the rooms will be heated regardless their occupation, but only during the dwelling occupied period from to 19:00 to 07:00 (EO 1); d) all the rooms will be heated regardless their occupation, but only during the dwelling occupied period from to 13:00 to 10:00 (EO 2); e) only the common area will be heated during the 24h period (CA 1); f) only the common area will be heated during the occupied period from 19:00 to 23:00 (CA 2); g) only the common area will be heated during the occupied period from 20:00 to 23:00 (CA 3); and during a specific period (from 09:00 to 24:00 in all the rooms and 24h in the bedrooms).

The *occupation patterns* refers to the occupied period and is defined as follows: a) the occupation schedule where occupants leave home in the early morning and arrive in the afternoon (WTO); b) the occupation schedule where occupants stay at home all day (ATH); c) the occupation schedule where occupants leave home in the early morning and arrive after lunch (MTO). In addition, the occupation patterns define the distribution of the households at home (e.g., occupants in the living room during the afternoon and in the bedrooms in the evening).

The *heating period* refers to the length of the heating during the winter season period. Eight periods were assumed: a) November to February; b) December to February; c) November to January; d) December to January; e) January; f) December; g) February; and h) winter season period. The length of the winter season period, for each geographical location, was dependent on the climate conditions. Based on ref. [72] (see subheading *bb)* in ANEXO II, Definições) heating period was defined from the first ten-days after 1st October, in which, for each geographical location, the daily mean temperature is below 15ºC, ending in the last ten-days before 31st May, in which the referred temperature is still below 15ºC.

As explicit in Table 22, the **heating period** (HP) is determined by the *heating period.* In Esp-r simulations, in the analysis of the results, one can choose the period of analysis. In RCCTE and REH´s building energy calculation models, the entire winter season is defined by default.

From Table 22, it is also possible to verify that the combination of the *occupation patterns* coupled with *heating schedules, household size and number of bedrooms occupied* result on different weekly heating patterns (i.e, which rooms are heated and when during a week). For each weekly heating patterns, a correspondent **percentage of heated area** (HA%) value was estimated, for each value of floor area. In Esp-r simulations, the percentage of heated area is introduced in the form of weekly heating patterns by designating set point temperatures values to each heated rooms during different heating periods, for each day type (weekdays, Saturday and Sunday) of the week. The RCCTE and REH´s building energy calculation models consider by default that all the rooms are heated all day long.

Also, when combinations of the *level of energy use, occupation patterns* and *household size* are coupled, different weekly[12] indoor heat gains patterns are defined. For each weekly indoor heat gains pattern, a correspondent average **indoor heat gains** (HG) value was estimated, for each value of floor area. In Esp-r simulations, the indoor heat gains are introduced in the form of weekly indoor heat gains patterns by designating hourly sensible and latent heat gains from equipment, people and lighting, for each day type of the week and rooms. The RCCTE and REH´s building energy calculation models define by default a constant value for indoor heat gains.

Due to the great amount of weekly heating patterns and indoor heat gains patterns defined for this work, just one example is illustrated for the case of an apartment 1F with a floor area of 100m^2. The apartment has the following characteristics: *W2 heating schedule; WTO occupation pattern; 2 bedrooms occupied; normal level of energy use; and 4 people living in the dwelling*, resulting in values of 29% and 4.5 W/m^2 for the HA% and HG, respectively. Table C.9, in Appendix C, presents the hourly sensible and latent heat gains per room from occupant, lighting and equipment, along with additional information, used to estimate the indoor heat gains, and Table C.10 presents the equipment used in each room, depending on the period of the day. Information on Table C.10 aided the estimation of the hourly sensible heat gains from equipment, shown in Table C.9. Taking the case of the apartment 1F as an example, Figure C.1 and Figure C. 2, in Appendix C, illustrate the heating patterns and indoor heat gains patterns for weekdays, for all the rooms in the dwelling, respectively.

[12]Simulations in EPS-r works primarily with weekly inputs that are reproduced for all the year.

The usefulness of capturing the influence of the OOB characteristics using heating patterns (HPat) (i.e., HP and HA%) and indoor heat gains (HG) lies on the fact that it enables to reduce the number of variables needed in the model, providing a more intuitive formulation.

110 combinations of the OOB characteristics were performed and resulted in a broad range of HPat and HG values that were assumed in the HEU simulations, especially because HA% and HG are floor area dependent. For example, for a particular combination of OOB characteristics, such as *W2 heating schedule; WTO occupation pattern; 2 bedrooms occupied; normal level of energy use; 4 people occupying the dwelling; and the entire winter season as the heating period*, the HA% and HG take values of 25% and 3.5 W/m^2, respectively, for a dwelling with 150m^2, and 29% and 4.5 W/m^2 for a dwelling with 100m^2 of floor area.

The range of HA% values obtained was between 4% and 100%; the HP varied between the possibilities that includes the entire winter season period and 1 to 4 months of heating period; the range of HG values varied between 1.4 and 12.0 W/m^2.

5.3 Description of variable database used in the statistical models

Figure 30 illustrates the main steps taken in the development of the statistical models.

The first step, which is the selection of the different possibilities within each category, was presented in the last sections (5.2.1 to 5.2.4).

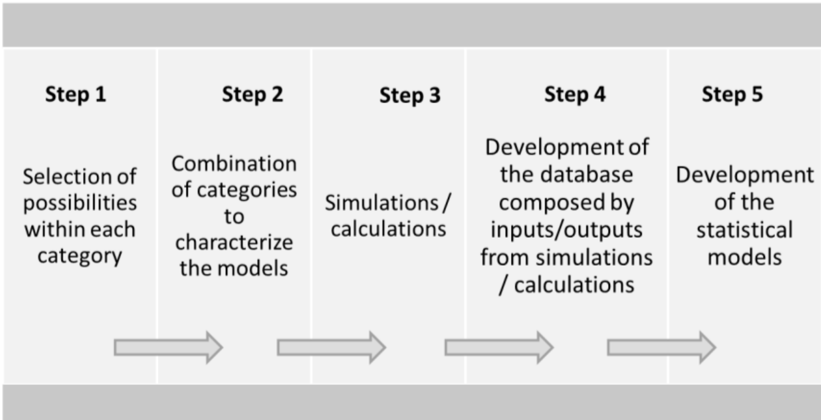

Figure 30. Main steps to the development of the statistical models.

As mentioned in section 5.2, the combination of different categories (i.e., building archetypes, geographical locations, set point temperature, heating patterns and indoor heat gains) characterized the building models constructed or considered in the HEU and $HDRC_{st}$ simulations and $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations. The inputs and the resultant outputs of those simulations/calculations built up the variable database used in the statistical models.

This section will describe the combinations of the different 5 categories used to characterize the building models for the simulations/calculations (Step 2) and the database resultant from these simulations/calculations (Step 4).

Two different approaches (A1 and A2) were used to combine the 5 categories. Each approach resulted on one different database. The universal and Portugal specific models for heating energy use (HEU) or set point temperature (Tsp) were developed using these two different databases. In this respect, Figure 31 illustrates the total number of models developed under this chapter (four universal models and eight Portugal specific models, i.e., four RCCTE specific models and four REH specific models).

In the first approach (A1), the HEU dataset resulted from 745 dynamic hourly simulations combining only the categories: building archetypes, geographical locations and set point temperatures. In the second approach (A2), the HEU dataset resulted from 2611 dynamic hourly simulations combining the categories: building archetypes, geographical locations, set point temperatures, heating patterns and indoor heat gains.

In both approaches, the three HDRC datasets (e.g. $HDRC_{st}$, $HDRC_{RCCTE}$, $HDRC_{REH}$) resulted from simulations or calculations (each) combining only the categories building archetypes and geographical locations, as set point temperature, heating patterns and indoor heat gains are reference values. The HDRC are replicated in the databases accordingly (as in Table shown in Figure 27) to perform the total number of observations included in HEU dataset.

The database in A1 includes 745 observations, while, in A2, the database totals 2611 observations.

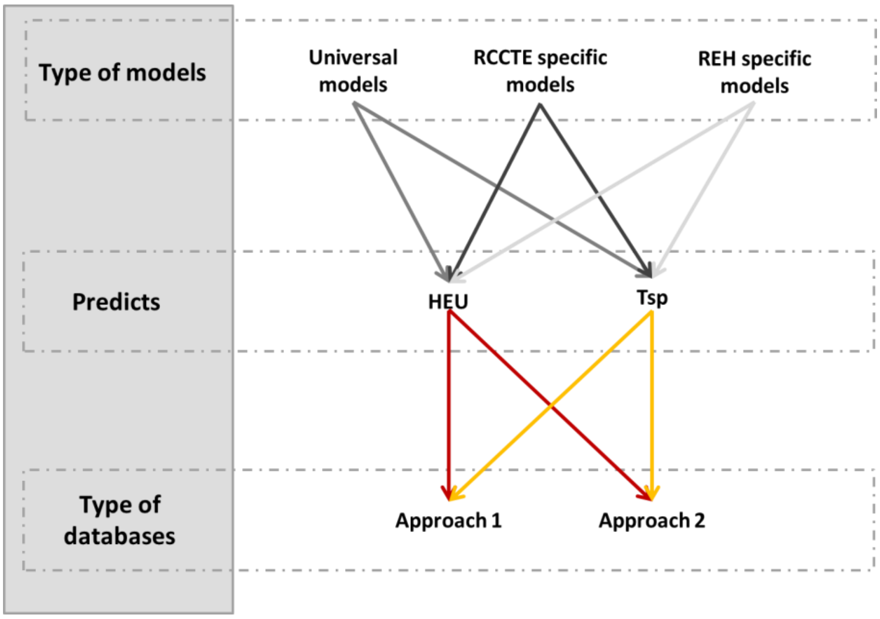

Figure 31. Schematization of the different models developed under chapter 5.

Table 23 summarizes all models developed and the characteristics of the databases for each approach, which will be discussed in more detail in the next sections 5.3.1 and 5.3.2.

Table 23. Summary of universal and Portugal specific models.

Model designation	Dependent variable	HEU dataset	HDRC dataset
		Approach A1	
$Model_{uni.}$ **HEU**.A1 $Model_{RCCTE}$ **HEU**.A1 $Model_{REH}$ **HEU**.A1	HEU predicting model	745 observations (28 building archetypes x 5 locations x maximum 6 of Tsp)	140 observations (28 building archetypes x 5 locations)
$Model_{uni.}$ **Tsp**.A1 $Model_{RCCTE}$ **Tsp**.A1 $Model_{REH}$ **Tsp**.A1	Tsp predicting model		
		Approach A2	
$Model_{uni.}$ **HEU**.A2 $Model_{RCCTE}$ **HEU**.A2 $Model_{REH}$ **HEU**.A2	HEU predicting model	2611 observations (267 building archetypes/Hpat/HG x maximum of 5 locations x maximum of 6 Tsp)	220 observations (44 building archetypes x 5 locations)
$Model_{uni.}$ **Tsp**.A2 $Model_{RCCTE}$ **Tsp**.A2 $Model_{REH}$ **Tsp_{sp}**.A2	Tsp predicting model		

5.3.1 Description of database: A1 - Varying only building archetype, geographical location and set point temperature

The first 28 building archetypes ([1-28], see Table 21, section 5.2.1) were combined with the 5 geographical locations (Manteigas, Bragança, Porto, Lisbon and Faro) to originate 140 combinations.

All the HEU simulations considered only one combination of the occupancy and occupant behaviour (OOB) characteristics from the 110 combinations selected (see section 5.2.4.2). Table 24 illustrates the OOB characteristics which reflected a range of different heating patterns (HPat) and indoor heat gains (HG) values, depending on the floor area of each one of the 28 building archetypes. The range of values were computed: the indoor heat gains (HG) values within the range of 1.4 to 4.5 W/m^2 and the percentage of heated area (HA%) in the range of 13% to 29%. The heating period (HP) was correspondent only to the entire winter season. Each one of the 140 combinations considered a particular value within the range of the HA% and HG values.

Table 24. Combination of OOB characteristics, in the first approach.

Heating Schedule	Occupation patterns	Level of energy use	Household size	No. bedrooms occupied	Heating period
W2	WTO	Normal	4	2	Winter season

(see Table 22 in section 5.2.4.2 for definitions.)

In particular, the 745 HEU simulations were performed by running each one of the 140 building models for a maximum of 6 set point temperature (Tsp) values (between 10ºC and 28ºC), which retrieved 745 observations to be analyzed.

The 140 $HDRC_{st}$ simulations were obtained by running the 140 building models at 20ºC. For the same combinations, the $HDRC_{RCCTE}$ and the $HDRC_{REH}$ calculations (140 each) assumed 20ºC and 18ºC, respectively. The assumed reference heating patterns ($HPat_{ref}$) and internal heat gains (HG_{ref}) values were as follows: the indoor heat gains (HG_{ref}) equal to 4 W/m^2, the percentage of heated area ($HA\%_{ref}$) equal to 100%, and the heating period (HP_{ref}) corresponded to the winter season period. It returned with 140 observations to be analysed.

The building models were characterized by combinations between different categories. Table 25 presents the possibilities within the different categories used in approach A1 to characterize the building models constructed/considered in the HEU and $HDRC_{st}$ simulations and in the $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations. Table 25 makes clear that the range of values of the 5 categories varies dependent whether they are building models for the simulations/calculations of HEU, $HDRC_{st}$, $HDRC_{RCCTE}$ or $HDRC_{REH}$.

Table 25. Comparison between the different possibilities within the categories used to characterize the building models for the HEU and $HDRC_{st}$ simulations, and $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations (Approach A1).

Categories that characterize the building models	 HEU simulations	 $HDRC_{st}$ simulations	 $HDRC_{RCCTE}$ calculations	 $HDRC_{REH}$ calculations
Building archetypes (M)	28 building archetypes	28 building archetypes, excepting constant IR_{ref} value (0.95ac/h)	Based on the 28 building archetypes. Differences in the calculation methods and in some of the values used	
Geographical locations (L)	Manteigas, Bragança, Porto, Lisbon, Faro using climate files based on RCCTE energy calculation model´s climate files		Manteigas, Bragança, Porto, Lisbon, Faro using energy calculation model´s climate files by default	
Set point temperature (Tsp)	**Tsp:** 10 to 28ºC	**Tsp_{ref}:** 20ºC	**Tsp_{ref}:** 20ºC	**Tsp_{ref}:** 18ºC
Heating patterns (HPat)	**HPat:**	**$HPat_{ref}$:**	**$HPat_{ref}$:**	**$HPat_{ref}$:**
% of heated area (HA%)	*HA% - 13% to 29%*	*$HA\%_{ref}$ - 100%*	*$HA\%_{ref}$ - 100%*	*$HA\%_{ref}$ - 100%*
Heating period (HP)	*HP - Winter season period*	*HP_{ref} - Winter season period*	*HP_{ref} - Winter season period, but might be defined differently from those assumed in simulations*	
Indoor heat gains (HG)	**HG:** *1.4 to 4.5 W/m^2*	**HG_{ref}:** *4 W/m^2*	**HG_{ref}:** *4 W/m^2*	**HG_{ref}:** *4 W/m^2*

The database was resultant from inputs/outputs of the HEU and $HDRC_{st}$ simulations, and $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations. Table 26 presents only the set of variables that constituted the database (in the first approach) used in the universal and Portugal specific statistical models developed to predict HEU (Eq. 5.3) or Tsp (Eq. 5.4).

Table 26. Set of variables for the universal and Portugal specific models developed to predict HEU or Tsp, for A1.

Variable name	Origin	Type of variable	Range of values	Universal predicting models		Portugal specific predicting models (RCCTE or REH specific models)	
				HEU	Tsp	HEU	Tsp
Tsp	Input HEU simulations	Continuous	10ºC to 28ºC	X		X	
HEU	Output HEU simulations	Continuous	2 to 224 kWh/m^2.year		X		X
$HDRC_{st}$*	Output $HDRC_{st}$ simulations	Continuous	14 to 266 kWh/m^2.year	X	X		
$HDRC_{RCCTE}$*	Output $HDRC_{RCCTE}$ calculations	Continuous	19 to 419 kWh/m^2.year			X	X
$HDRC_{REH}$*	Output $HDRC_{REH}$ calculations	Continuous	3 to 286 kWh/m^2.year			X	X

*To note that the range of $HDRC_{st}$ values are equivalent to those of $HDRC_{RCCTE}$ and $HDRC_{REH.}$

5.3.2 Description of database: A2 - Varying building archetypes, geographical locations, set point temperature, heating patterns and indoor heat gains

This approach used 16 additional building archetypes ([1-44], see Table 21, section 5.2.1). Herein, the *air infiltration rates/natural ventilation* and *type of urbanization* vary.

For the HEU simulations, the 44 building archetypes were combined with some of the 110 combinations of occupancy and occupant behaviour (OOB) characteristics selected (see section 5.2.4.2), yielding 267 different combinations. These are presented in Table C.11, in Appendix C.

The range of possible heating patterns (HPat) and indoor heat gains (HG) values were computed from the vast combinations of OOB characteristics, depending on the floor area of each one of the 44 building archetypes. The range of values computed were: the HG values were in the range of 1.4 to 12.0 W/m^2 and the HA% values, between the range of 4% and 100%. The HP can last all the winter season period, or 1 to 4 months. Each one of the 267 combinations considered a particular value within the range of the HA% and HG values.

The 267 combinations combined with a maximum of 5 geographical locations (Manteigas, Bragança, Porto, Lisbon, Faro) resulted in 728 different models. The 2611 HEU simulations were then performed by running the 728 building models for a maximum of 6 set point temperature (Tsp) values (between 10ºC and 28ºC), totaling 2611 observations.

For the three HDRC datasets, the combination of the 44 building archetypes with 5 geographical locations totals 220 different combinations. The 220 $HDRC_{st}$ simulations were obtained by running the 220 building models at 20ºC. The $HDRC_{RCCTE}$ and the $HDRC_{REH}$ calculations (220 each) were resultant from using the models at 20ºC and 18ºC, respectively. Again, for each one of the models, the indoor heat gains (HG_{ref}) was assumed to be 4 W/m^2, the percentage of heated area ($HA\%_{ref}$) 100%, and the heating period (HP_{ref}) is correspondent to the winter season period.

The building models were characterized by combinations between different categories. Table 27 presents the possibilities within the different categories used in approach A2 to characterize the building models constructed/considered in the HEU and $HDRC_{st}$ simulations and $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations. Table 27 makes clear the differences in the range of values of the 5 categories between building models for the simulations/calculations of HEU, $HDRC_{st}$, $HDRC_{RCCTE}$ or $HDRC_{REH}$.

Table 27. Comparison between the different possibilities within the categories used to characterize the building models for the HEU and $HDRC_{st}$ simulations, and $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations (Approach A2).

Categories that constitute the characteristics of building models	 **HEU simulations**	 **$HDRC_{st}$ simulations**	 **$HDRC_{RCCTE}$ calculations**	 **$HDRC_{REH}$ calculations**
Building archetypes (M)	44 building archetypes	44 building archetypes, excepting constant IR_{ref} value (0.95ac/h)	Based on the 44 building archetypes. Differences in the calculation methods and in some of the values used	
Geographical locations (L)	Manteigas, Bragança, Porto, Lisbon, Faro using climate files based on RCCTE energy calculation model´s climate files		Manteigas, Bragança, Porto, Lisbon, Faro using energy calculation model´s climate files by default	
Set point temperature (Tsp)	**Tsp:** 10 to 28ºC	**Tsp_{ref}:** 20ºC	**Tsp_{ref}:** 20ºC	**Tsp_{ref}:** 18ºC
Heating patterns (HPat)	**HPat:**	**$HPat_{ref}$:**	**$HPat_{ref}$:**	**$HPat_{ref}$:**
% of heated area (HA%)	*HA% - 4% to 100%*	*$HA\%_{ref}$ - 100%*	*$HA\%_{ref}$ - 100%*	*$HA\%_{ref}$ - 100%*
Heating period (HP)	*HP - Winter season period; 1 to 4 months*	*HP_{ref} - Winter season period*	*HP_{ref} - Winter season period, but might be defined differently from those assumed in simulations*	
Indoor heat gains (HG)	**HG:** *1.4 to 12.0 W/m^2*	**HG_{ref}:** *4 W/m^2*	**HG_{ref}:** *4 W/m^2*	**HG_{ref}:** *4 W/m^2*

The database was resultant from inputs/outputs of the HEU and $HDRC_{st}$ simulations, and $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations. Table 28 presents the set of variables that constituted the database (in the second approach) used in the universal and Portugal specific statistical models developed to predict HEU (Eq. 5.3) or Tsp (Eq. 5.4). In addition, Table 28 presents the values of the independent variables *HA%, HP, HG*, and *IR*, which correspond to inputs to HEU simulations. These variables were used to improve the performance of the models developed (based on Eq. 5.2) as they aid explaining the heating patterns (HA% and HP), indoor heat gains (HG) and air infiltration rate/natural ventilation (IR) values assumed in HEU simulations (when reference values $HA\%_{ref}$, HG_{ref}, IR_{ref}, HP_{ref} from HDRC don´t). Note that *IR* is one of the physical characteristics of the building archetypes (M) (see Table 20) and therefore is not directly discriminated in Eq. 5.2. Furthermore, it presents the range of values in which each variable varies.

Table 28. Set of variables for the universal and Portugal specific models developed to predict HEU or Tsp, for A2.

Variable name	Origin	Type of variable	Range of values	Universal predicting models		Portugal specific predicting models (RCCTE or REH specific models)	
				HEU	Tsp	HEU	Tsp
Tsp	Input HEU simulations	Continuous	10ºC to 28ºC	X		X	
HEU	Output HEU simulations	Continuous	1 to 621 kWh/m^2.year		X		X
$HDRC_{st}$	Output $HDRC_{st}$ simulations	Continuous	14 to 266 kWh/m^2.year	X	X		
$HDRC_{RCCTE}$	Output $HDRC_{RCCTE}$ calculations	Continuous	19 to 419 kWh/m^2.year			X	X
$HDRC_{REH}$	Output $HDRC_{REH}$ calculations	Continuous	3 to 286 kWh/m^2.year			X	X
HA%	Input HEU simulations	Continuous	*4% to 100%*	X	X	X	X
HG	Input HEU simulations	Continuous	*1.4 to 12.0 W/m^2*	X	X	X	X
HP	Input HEU simulations	Ordinal	1 to 8[a]	X	X	X	X
IR	Input HEU simulations	Continuous	0.6 to 1.7 ac/h	X	X	X	X

[a]1 – February; 2 – December; 3 – January; 4 – December to January; 5 – November to January; 6 – December to February; 7 – November to February; 8 – Winter season period.

5.4 Description of the statistical models

5.4.1 Statistical models

The universal and the Portugal specific models were developed employing the following statistical methods: a) multivariate regression and b) artificial neural networks. These are thought to be the most suitable for the development of the models in this chapter and specifications are detailed in the next sections below.

5.4.1.1 Multivariate regression

Regression analysis is a technique used to analyze data with a dependent variable and one (univariate) or more (multivariate) independent variables. The dependent variable is modeled as a function of independent variables, estimating the regression coefficients for each variable and an error term. The error term represents unexplained variation in the dependent variable and is treated as a random variable. The regression coefficients values are estimated in such a way that provide the 'best fit' to the data. The most commonly used method to estimate regression coefficients is the least squares method [161].

Multivariate regression analysis is one of the most common methodologies used to analyze the dependency of a variable on a set of independent variables [270]. Multivariate regression is one of the most common methodologies used to analyze the dependency of a variable on a set of independent variables [270]. The multivariate regression used is depicted in Eq. 5.6. It assumes that the dependent variable *(Y)* can be explained by a linear function of *xr* (r=1,..., m) independent variables.

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_r x_r + e \qquad \text{Eq. 5.6}$$

where, β_r (r = 1,..., m) are the regression coefficients to be estimated; and *e* represents the error term with a distribution N $(0,\sigma_e^2)$.

The square of a set of independent variables (e.g., Tsp, $HDRC_{st}$) were also used in order to analyze nonlinear relationships between *Y* and these variables. The multivariate regression that includes squared variables is called nonlinear regression, hereafter.

The multivariate regression analyses were developed using the software SPSS [271]. The database was randomly divided as training (75%) and testing (25%) datasets. The model was calibrated using the training dataset. A sensitivity analysis was made to the regression models by eliminating variables with less explanatory power [272]. The model was tested by applying the accuracy metrics (section 5.4.2) in the testing dataset. The final models used are explained in detail in sections 5.5 and 5.6.

5.4.1.2 Artificial neural networks

Artificial neural networks (ANN) have been successfully used in many fields [190,273–276], such as in the context of energy management [190].

An artificial neural network (ANN) is an information-processing system that has certain performance characteristics in common with biological neural networks [272]. An ANN is able to learn from examples, storing the experimental knowledge for use when required. However, the development of a typical ANN architecture requires a specific understanding of how it can be applied to obtain the desired performance [190]. The capabilities and advantages of ANNs are widely known, such as the resistance to errors and noise [190].

Figure 32 illustrates the procedure behind an ANN. The ANN can be trained to perform a particular function by adjusting the values of the connections (weights) between elements.

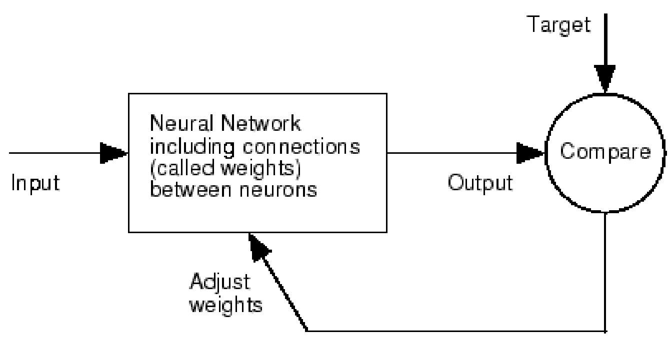

Figure 32. Neural networks overview [Source:[277]].

In this chapter, the ANN analyses were developed using the Neural Toolbox in MATLAB R2014b software [277]. For modeling the problem using an ANN, a feedforward multilayer neural network with a back-propagation technique was used.

A feedforward multilayer neural network consists of an input layer, one or more hidden layers, and an output layer. In this work, a single hidden layer was considered to map the function provided suitable hidden neurons. The hidden layer assists to solve non-linear separable problems [199].

In particular, a three-layer feedforward network (one input layer, one hidden layer and one output layer), with a nonlinear activation function in the hidden layer and a linear function in the output layer (see Figure 33), was used. The ANN was trained applying the Levenberg-Marquardt algorithm [278].

The selection of the algorithm depends on many factors, including the complexity of the problem, the number of observations in the training set, the number of weights and biases in the network, the error goal, and the type of use (classification or regression). In this study, Levenberg-Marquardt algorithm was used as it is one of the fastest training functions, and it is suitable to be used in not very large networks (i.e, with thousands of weights) [279]. It is also the default training function for feedforward net in the neural toolbox. Other algorithms were tested (e.g., BFGS Quasi-Newton and Resilient Backpropagation) and they perform worse than the Levenberg-Marquardt algorithm.

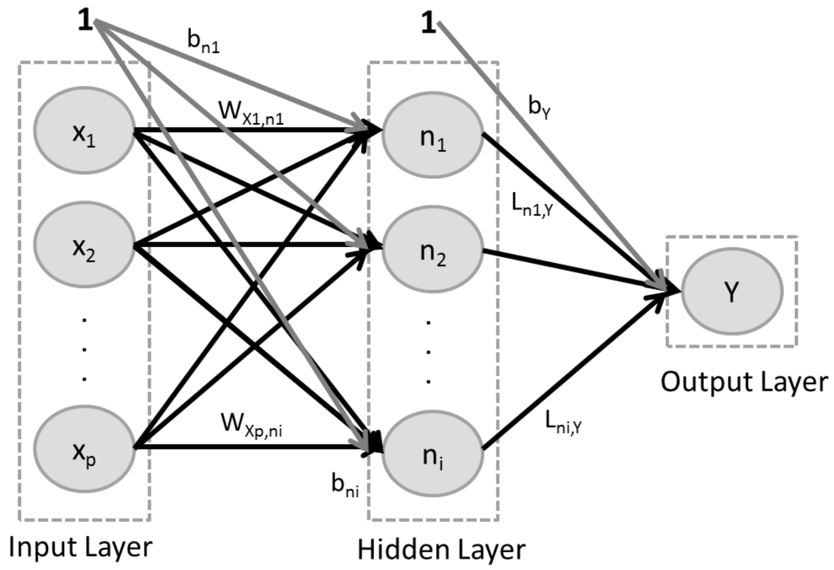

Figure 33. Schematic of a three-layer feedforward network [Based on Ref. [186]].

In Figure 33, *X (X= 1, .., Xp)* represents the different independent variables applied to the training model; *n (n= 1, …,* n_i*)* represents the number of neurons applied to the training model and *Y* represents the target (i.e., dependent variable) of the training model. For the nonlinear activation function (i.e, first function), each *X* is connected to each neuron *n* through weight values (*W*). Each neuron has a bias *b*, which is summed with the weighted values as described by the following equation:

$$n_i = W_{X1,ni} + W_{X2,ni} + \cdots + W_{XP,ni} + b_i \quad \text{Eq. 5.7}$$

In the linear function (i.e., the second function), each neuron is connected to the target *Y* by weight values (*L*). The target *Y* has also a bias b_Y associated, which is summed with the weighted values as described by the following equation:

$$Y = L_{n1,Y} + L_{n2,Y} + \cdots + L_{ni,Y} + b_Y \quad \text{Eq. 5.8}$$

There are no clear rules to choose the 'best' number of hidden nodes. Network design is a trial-and-error process and may affect the accuracy of the model. The models were tested for different number of hidden neurons using the constructive method. First, it was tested a small

ANN, and then neurons were added until reaching better accuracy values. Note that all variables were normalized to fall between -1 and 1 in order to achieve faster convergence and better accuracy.

The process of training involved tuning the values of the weights and biases of the network to optimize network performance, using the mean square error (MSE) as the default performance function [279].

In this work, database was randomly divided into training (50%), validation (25%) and testing (25%) datasets to provide generalization to the model. Training dataset is used to learn the behaviour of input data and to adjust the model coefficients. It was selected the best evaluation criterion (the mean square error (MSE)) of 100 training runs. Validation dataset is used to control the overfitting (overfitting occurs when a statistical model describes random error or noise instead of the underlying relationship). Testing dataset is used to evaluate the models by applying the accuracy metrics (section 5.4.2) [199]. The final models used are explained in detail in sections 5.5 and 5.6.

5.4.2 Performance evaluation of the models

Four accuracy metrics were used to evaluate the goodness of fit of the regression and the ANN models. The first is the coefficient of determination (R^2) (predictive R^2), which indicates how closely predicted values match the actual values. R^2 can be calculated as in Eq. 5.9 [199].

$$R^2 = \frac{\sum_{i=1}^{n}\left[y_{predicted} - \bar{y}_{observed}\right]^2}{\sum_{i=1}^{n}\left[y_{observed} - \bar{y}_{observed}\right]^2.} \quad i = 1,2,\ldots n \qquad \text{Eq. 5.9}$$

where, $y_{observed}$ is the observed values, $\bar{y}_{observed}$ is the average observed values; $y_{predicted}$ is the predicted values and *n* stands for the total number of observations.

The following metrics evaluate the magnitude of the errors between the observed and predicted values. The mean square error (MSE) can be described by Eq. 5.10 [149,199,254]:

$$MSE = \frac{\sum_{i=1}^{n}\left[y_{observed} - y_{predicted}\right]^2}{n} \quad i = 1,2,\dots n \qquad \text{Eq. 5.10}$$

where, $y_{observed}$ is the observed values and $y_{predicted}$ is the predicted values and *n* stands for the total number of observations.

This accuracy metrics is introduced in this analysis because the neural network run by MATLAB uses the MSE [199,272,280] as an evaluation criterion of the trained network.

The other two accuracy metrics correspond to the mean absolute error (MAE), which was introduced in section 4.3.1, and the mean absolute percent error (MAPE).

Percentage errors have the advantage of being scale-independent, and so are frequently used to compare performance between different models. Many organizations focus primarily on MAPE [158,170,254,256] when assessing forecast accuracy. Also, most people are comfortable thinking in percentage terms, making the MAPE easy to interpret. MAPE suits the modeling analysis developed in this chapter as it involves a great amount of data that is guaranteed to be strictly positive [255]. Because percentage errors assume a meaningful zero, a percentage error makes no sense when measuring the accuracy of temperature predictions on the Fahrenheit or Celsius scales[281].

The MAPE accuracy metric can be calculated using Eq. 5.11.

$$MAPE = \frac{\sum_{i=1}^{n}\left\|\frac{y_{observed} - y_{predicted}}{y_{observed}}\right\|}{n} \times 100 \quad i = 1,2,\dots n\ [\%] \qquad \text{Eq. 5.11}$$

where, $y_{observed}$ is the observed values and $y_{predicted}$ is the predicted values and *n* stands for the total number of observations.

The 'best' model is the one that gathers the minimum values of error metrics and the highest values of R^2.

5.5 Development of the universal models

The universal HEU or Tsp predicting models were developed using two approaches (A1 and A2), considering each two different databases (see Table 26, section 5.3.1 and Table 28, section 5.3.2, respectively).

In this research, four universal models (see Table 23, in section 5.3) were developed: $Model_{uni.}$ HEU.A1; $Model_{uni.}$ Tsp.A1; $Model_{uni.}$ HEU.A2 and $Model_{uni.}$ Tsp.A2.

The models developed in the approach A1 are limited to a more narrow range of heating patterns (HPat) and indoor heat gains (HG) scenarios (see, Table 25, second column, in section 5.3.1).

In turn, the models developed in the approach A2 can be applied to a broad range of situations (see Table 27, second column, section 5.3.2). However, these models require a higher level of expertise and knowledge in statistical modeling.

In the approach A1, the universal modeling of HEU ($Model_{uni.}$ HEU.A1) and of Tsp ($Model_{uni.}$ Tsp.A1) were developed applying multivariate regression.

In the approach A2, more sophisticated techniques were employed in order to improve the performance of the models due to the nature and size of the database. Firstly, the universal modeling of HEU ($Model_{uni.}$ HEU.A2) was developed applying the multivariate regression analysis and also ANN models. Secondly, these models were extended using an additional set of independent variables (*HA%, HP, HG, IR*), as illustrated by Equations 5.12 and 5.13. This set of variables represents inputs to HEU simulations (see Table 28). The modeling of Tsp ($Model_{uni.}$ Tsp.A2) was developed applying only ANN analysis, using Eq. 5.14.

$$HEU = f(HDRC, Tsp, HA\%, HG, HP) \qquad [kWh/m^2.year] \qquad \text{Eq. 5.12}$$

$$HEU = f(HDRC, Tsp, HA\%, HG, HP, IR) \qquad [kWh/m^2.year] \qquad \text{Eq. 5.13}$$

$$Tsp = f(HDRC, HEU, HA\%, HG, HP, IR) \qquad [ºC] \qquad \text{Eq. 5.14}$$

where, *HDRC* is the theoretical heating demand under reference conditions; and *HA%* is the percentage of heated area, *HG* is the indoor heat gains (W/m^2), *HP* is the heating period and the *IR* is the air infiltration rate/natural ventilation (ac/h) input values assumed in the HEU simulations. HEU is the heating energy use in terms of 'useful' energy.

Table 29 summarizes the best performing models among all the models performed. In particular, it reports, for each predicting model analyzed (first column), the statistical analyses conducted (Multivariate linear regression – MLR; Multivariate non-linear regression – MNLR; and Artificial neural networks - ANN), the accuracy metrics (R^2, MAE, MAPE, MSE), the number of neurons used in the ANN, and the dependent and independent variables. MAE is used in terms of kWh/m^2.year for the HEU predicting values, and in terms of ºC for the Tsp predicting values.

Table 29. Results of universal models (A1 and A2).

Predicting Models	Statistical models	Testing accuracy metrics				No. of neurons	Dependent variable	Independent variables
		R^2	MAE	MAPE	MSE			
				ApproachA1				
Model$_{uni.}$ HEU.A1	MLR	0.774	13.4	159%	2.7.E+02	-----	HEU	**Tsp*; $HDRC_{st}$***
	MNLR	**0.930**	**6.3**	**42%**	**7.7E+01**	-----	**HEU**	**Tsp*; $HDRC_{st}$; Tsp^2; $HDRC_{st}^2$; Tsp.$HDRC_{st}$; Tsp.$HDRC_{st}^2$; Tsp^2.$HDRC_{st}$*; Tsp^2.$HDRC_{st}^2$***
Model$_{uni.}$ Tsp.A1	MNLR	0.910	1.8	------	2.4E+00	-----	Tsp	HEU*; $HDCR_{st}$*; HEU^2*; HEU.$HDRC_{st}$*; HEU^2.$HDRC_{st}$*; $HDRC^2$*;HEU^2.$HDRC_{st}^2$*; HEU.$HDRC_{st}^2$
				ApproachA2				
Model$_{uni.}$ HEU. A2	MNLR	0.511	29.0	238%	2.5E+03	-----	HEU	Tsp; $HDRC_{st}$*; Tsp^2; $HDRC_{st}^2$; Tsp.$HDRC_{st}$*; Tsp.$HDRC_{st}^2$; Tsp^2.HDRC; Tsp^2.$HDRC_{st}^2$
	ANN	0.489	32.6	244%	2.8E+03	5	HEU	$HDRC_{st}$; Tsp
	ANN	0.353	33.9	294%	3.5E+03	22	HEU	$HDRC_{st}$; Tsp
	MNLR	0.889	14.9	132%	5.5E+02	-----	HEU	Tsp; $HDRC_{st}$*; HA%*; HG*; HP*; Tsp^2; $HDRC_{st}^2$; $HA\%^2$; Tsp.$HDRC_{st}$; Tsp.HA%; Tsp.HG; Tsp.HP; Tsp.$HDRC_{st}^2$; Tsp.$HA\%^2$; Tsp^2.$HDRC_{st}$*; Tsp^2.HA%*; Tsp^2.HP; Tsp^2.HG*; Tsp^2.$HDRC_{st}^2$; Tsp^2.$HA\%^2$; $HDRC_{st}$.HA%*; $HDRC_{st}$.HG*; $HDRC_{st}$.HP; $HDRC_{st}$.$HA\%^2$*; $HDRC_{st}$.HG; $HDRC_{st}$.HP; $HDRC_{st}^2$.HA%*; $HDRC_{st}^2$.HG; $HDRC_{st}^2$.HP; $HDRC_{st}^2$.$HA\%^2$; HA%.HG*; HA%.HP; $HA\%^2$.HG*; $HA\%^2$.HP; HG.HP
	ANN	0.970	7.1	51%	2.E+02	9	HEU	$HDRC_{st,}$ Tsp, HA%, HG, HP
	ANN	**0.988**	**4.9**	**45%**	**6.7E+01**	**13**	**HEU**	**$HDRC_{st,}$ Tsp, HA%, HG, HP, IR**
Model$_{uni.}$ Tsp. A2	**ANN**	**0.966**	**0.7**	----	**9.7E-01**	**15**	**Tsp**	**$HDRC_{st,}$ Tsp, HA%, HG, HP, IR**

Only for regression statistical models: significant at 1%: *; significant at 5%: **.

Analysing Table 29 it is possible to conclude that three of the four models proposed with universal applicability (shaded in grey) revealed to be good predicting models. These are:

a) the model to predict HEU using the first approach: only varying physical characteristics of the building archetypes and geographical locations ($Model_{uni}$. HEU.A1, MNLR statistical model);
b) the model to predict HEU using the second approach: varying physical characteristics of the building archetypes and geographical locations and occupancy and occupant's behaviour (OOB) characteristics ($Model_{uni.}$ HEU.A2, ANN statistical model);
c) the model to predict Tsp using the second approach: varying both physical characteristics of the building archetypes and geographical locations and OOB characteristics ($Model_{uni.}$ Tsp.A2, ANN statistical model).

The coefficients of determination (R^2) of the three best statistical models are close or even higher that most values found in the literature. For example, Kialashaki and Reisel [272] developed three models for predicting energy demand of the residential sector of USA using ANN statistical models. The respective R^2 values were 0.9823, 0.9849 and 0.9896. Paudel *et al.* [199] obtained a R^2 of 0.85 for the building heating energy demand ANN model. Buratti *et al.* [191] in developing an ANN model obtained a R^2 of 0.9957. Also, Aydinalp *et al.* [166] developed a ANN model for modeling space heating energy demand in the residential sector obtained a R^2 of 0.908. The empirical studies that applied standard linear regression presented lower R^2 values. This is the case of Kelly (2011) [259], who presented a model with an adjusted R^2 of 0.314. Another example is the finding achieved by Santin *et al.* (2009) [63], which modeled energy use as a function of the building characteristics and achieved a R^2 equal to 0.42.

The manifested errors are probably mainly derived from the differences between the values taken for the different categories (i.e., building archetypes, geographical locations, set point temperature, heating patterns and indoor heat gains) that characterized the building models used in the HEU and $HDRC_{st}$ simulations. Because databases from approach A1 and A2 were resultant from different combinations of categories, errors might have different origins depending on the approach used to build up the database.

In approach A1 (see Table 25, section 5.3.1) errors resulted mainly from HEU simulations assuming heating patterns, indoor heat gains and air infiltration rate/natural ventilation values particularly distinct from the reference values assumed in the $HDRC_{st}$ simulations.

The approach A2 (see Table 27, section 5.3.2) attempted to cope with the issue intrinsic to models developed under A1 by including additional independent variables (*IR, HA%, HP, HG*) to explain better the HEU. Still, part of the errors might also be explained by the limitation inherent to the use of variables in the statistical models that do not account neither with the effect of orientation of the heated spaces nor with the period of heating during the day on the heating energy use. This might be relevant as solar gains and thermal losses vary during the day and depend on the orientation of the dwelling.

This is the case of the variables *IR* and *Tsp*. For example, for a building archetype with a specific orientation, assuming a *Tsp* value of 20ºC or an *IR* value of 1.3ac/h in the statistical model, the model would predict a certain value of HEU, regardless, if the heated rooms are oriented towards South or North and heated during the morning or evening. The same issue is extended to the variables *HG* and *HA%*.

An in depth analysis regarding the development of the three predicting models is presented next:

Concerning the model for predicting HEU using the approach A1 - **$Model_{uni}$. HEU.A1**, the analysis of the errors, measured through the accuracy metrics (MAE, MAPE and MSE) and the R^2, indicated that the MNLR statistical model perform better than the corresponding MLR statistical model.

The MNLR model predicts relatively well HEU using the *Tsp* and *$HDRC_{st}$*, and other independent variables as presented in Table 29, with a R^2 of 0.93.

All the detailed results regarding the MNLR statistical model are presented in Appendix C (parameter estimates in Table C.12; comparison between observed and predicted values, using the testing dataset in Figure C.3).

In the attempt to develop models to predict HEU using the approach A2 - **Model$_{uni.}$ HEU.A2**, six models varying in type of statistical model and independent variables were developed. The evaluation of the accuracy metrics brings the conclusion that none of three first models are particularly effective at predicting the HEU using only the independent variables $HDRC_{st.}$ and *Tsp*. This may be an indication that the increase of observations with a large variety in terms of heating patterns (HPat) and internal heat gains (HG) input values in the HEU simulations led to models with worse performance. A possible explanation for this performance is that the independent variables $HDRC_{st}$ and *Tsp* together no longer explain adequately the wide variation of HEU values, especially because $HDRC_{st}$ assumes single reference values for the $HPat_{ref}$ and HG_{ref}. This can also be explained by the different air infiltration rates/natural ventilation values assumed in both HEU and $HDRC_{st}$ simulations (the latter assumed a reference value (IR_{ref})).

Therefore, there was the need to consider an extended Model$_{uni}$. HEU.A2 with further independent variables to better explain HEU values. The variables introduced in the model were: the two components of heating patterns (*HA%* and *HP*), the internal heat gains (*HG*) and the air infiltration rates/natural ventilation (*IR*). The relationships illustrated in Eq. 5.12 and 5.13 were thus analyzed using MNLR and ANN statistical models.

From these three last models, it is possible to conclude that the two ANN models are the most promising models to predict the HEU values as they have better accuracy results than regression analyses (see Table 29). The ability of ANN in performing non-linear analysis is therefore an advantage [256] towards the multivariate regression analysis. Because of the learning properties of the ANN model and its sensitivity to fluctuations of the independent variables, the performance of the ANN model is clearly better than the regression models and the results generated by the ANN model are closer to the actual observed data [189].

Furthermore, it can be concluded that variable IR improves the prediction ability of the ANN model, exhibiting higher R^2 and lower errors than the ANN model in the absence the *IR* variable. Therefore, the best model to predict HEU is an ANN statistical model using the variables HDRCst, Tsp, HA%, HP, HG and IR (R2 equal to 0.988). In the end, it can be concluded that the relationship characterized by Eq. 5.13 is therefore the most appropriate to predict HEU over the Eq. 5.3 initially considered.

All the detailed results regarding the ANN statistical model are presented in Appendix C (comparison between observed and predicted values, using the testing dataset, in Figure C.4).

A similar model to the one selected for HEU using approach A2 was tested to predict Tsp - **$Model_{uni.}$ Tsp.A2**, using Eq.5.14.

From Table 29, it can be concluded that the ANN performs well with the variables *$HDRC_{st}$, Tsp, HA%, HG, HP* and *IR*, presenting a high R^2 of 0.966 and low errors. It can be concluded that the relationship characterized by Eq. 5.14 is therefore the most appropriate to predict HEU over the Eq. 5.4 initially considered.

All the detailed results regarding the ANN statistical model are presented in Appendix C (comparison between observed and predicted values, using the testing dataset, in Figure C.5).

The results of Tsp prediction models should be analyzed with care as the *Tsp* variable was considered as a discrete variable. In order to reflect the original nature of the variable, new HEU simulations are suggested to be conducted assuming continuous values. These values should be then included in the Tsp prediction models.

5.5.1 Example of the applicability of universal models: Portugal

The practicality of the universal models can be enhanced in different geographical contexts, such as different countries. Countries might have different methods to calculate HDRC values, which may differ from the standard $HDRC_{st}$ assumed in the universal models. To overcome this difference, HDRC values issued in building certificates need to be converted into $HDRC_{st}$ values, using, for instance, a regression model. A simple demonstration of this conversion was done for the HDRC values derived from the former RCCTE Portuguese regulation ($HDRC_{RCCTE}$)[13].

For a set of building archetypes and geographical locations, the $HDRC_{st.}$ output values were obtained from dynamic thermal building simulations run in ESP-r at reference conditions assumed in this work (see Table 30). In turn, using the same set of building archetypes and geographical locations, the $HDRC_{RCCTE}$ output values were computed under RCCTE reference conditions, using the RCCTE regulation´s energy calculation model [72].

[13] The $HDRC_{RCCTE}$ values are entitled as nominal heating needs (Nic) in the RCCTE regulation.

Table 30. Reference $HDRC_{st}$ values.

Variables	Values
Reference air infiltration rate/natural ventilation (IR_{ref})	0.95ac/h
Reference set point temperature (Tsp_{ref})	20ºC
Reference heating patterns ($HPat_{ref}$)	
% of heated area ($HA\%_{ref}$)	*100%*
Heating period (HP_{ref})	*Winter season period*
Reference indoor heat gains (HG_{ref})	*4 W/m²*

As previously mentioned, the length of the winter season period, for each geographical location, was dependent on the climate conditions. Based on ref. [72] (see subheading bb) in ANEXO II, Definições) winter season period was defined from the first ten-days after 1st October, in which, for each geographical location, the daily mean temperature is below 15ºC, ending in the last ten-days before 31st May, in which the referred temperature is still below 15ºC.

The model that relates the $HDRC_{st}$ simulation and the $HDRC_{RCCTE}$ calculation output values is described in Eq. 5.15. In the case of Portugal, this relationship presents a high coefficient of determination (R^2=0.906) as it can be verified by Figure 34.

$$HDRC_{st} = 5.27E^{-1} \times HDRC_{RCCTE} + 15.566 \quad [kWh/m^2.year] \qquad \text{Eq. 5.15}$$

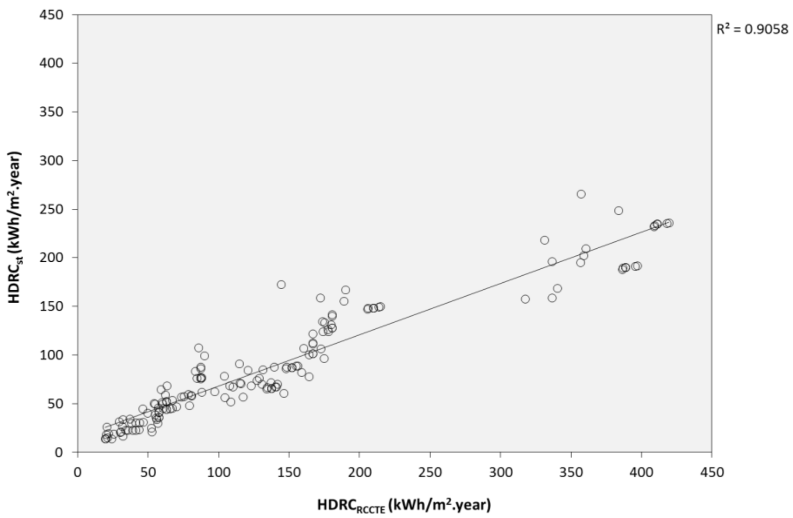

Figure 34. Comparison between the $HDRC_{st}$ and $HDRC_{RCCTE}$ values.

By using this relation, the values of HDRC shown in the RCCTE energy performance certificates (or calculated under its scheme or any other methodologies used to calculate $HDRC_{RCCTE}$) can be used to estimate values of $HDRC_{st}$ and then to make use of the $HDRC_{st}$-Tsp-HEU models, avoiding the need to perform simulation of any specific building. In principle, similar relationships could be developed for any other EPC scheme or country.

In case of any future improvements to the EPBD approach or of any other EPC scheme that would imply changes to their energy calculation methodologies, these models can still be used, as long as new conversion relationship is established between the standard $HDRC_{st}$ and the new HDRC values issued.

5.6 Development of Portugal specific models

This section has the same aim as section 5.5.1 of enabling the use of the energy certificates to enable a HDRC-Tsp-HEU analyses. However it does so from a more upstream approach, by using directly the values of HDRC coming from the certificates to develop the statistical model, instead of applying a patch-like approach as was the case of section 5.5.1. While this has the disadvantage of the results being representative only for Portugal, it has the advantage of providing a statistically sounder model. A similar development could however, in principle, be made for any other country.

In the Portugal specific models, the HEU or Tsp can be predicted applying the $HDRC_{RCCTE}$ or $HDRC_{REH}$ values extracted from the energy performance certificates issued and registered in the Portuguese EPC database.

The models were developed using two approaches (A1 and A2), considering each two different databases (see Table 26, section 5.3.1 and Table 28, section 5.3.2, respectively).

In this research, it was developed eight Portugal specific models (see Table 23, in section 5.3).

The eight models were developed using the most promising techniques revealed when modeling the universal models. In particular, in the approach A1, the HEU modeling ($Model_{RCCTE}$ HEU.A1 and $Model_{REH}$ HEU.A1) was developed applying the multivariate non-linear regression (MNLR). The MNLR analysis was also applied for modeling Tsp ($Model_{RCCTE}$. Tsp.A1 and $Model_{REH}$. Tsp.A1).

In the approach A2, the HEU modeling ($Model_{RCCTE}$. HEU.A2 and $Model_{REH}$. HEU.A2) was developed applying the artificial neural networks (ANN), considering the whole set of independent variables (*HA%, HG, HP, IR*). In addition, artificial neural networks were applied in the modeling of Tsp ($Model_{RCCTE}$. Tsp.A2 and $Model_{REH}$. Tsp.A2).

Table 31summarizes the best performing models among all the models performed. In particular, it reports, for each predicting model analyzed (first column), the statistical models analyzed (Multivariate non-linear regression – MNLR; and Artificial neural networks - ANN), the accuracy metrics (R^2, MAE, MAPE MSE), the number of neurons used in the ANN, and the dependent and independent variables. MAE is used in terms of kWh/m^2.year for the HEU predicting values, and in terms of ºC for the Tsp predicting values.

Table 31. Results of Portugal specific models (A1 and A2).

Predicting Models	Statistical Models	Testing				No. of neurons	Dependent variable	Independent variables
		R^2	MAE	MAPE	MSE			
				ApproachA1				
$Model_{RCCTE}$. HEU.A1	MNLR	0.840	9.2	62%	1.8.E+02	-----	HEU	Tsp; $HDRC_{RCCTE}$; Tsp^2*; Tsp.$HDRC_{RCCTE}$*Tsp^2.$HDRC_{RCCTE}$*
$Model_{REH}$. HEU.A1	MNLR	0.779	11.1	82%	2.4.E+02	-----	HEU	Tsp; $HDRC_{REH}$; Tsp^2*; Tsp.$HDRC_{REH}$*Tsp^2.$HDRC_{REH}$*
$Model_{RCCTE}$. Tsp.A1	MNLR	0.844	1.7	-----	4.0.E+00	-----	Tsp	HEU*; HEU^2*; $HDRC_{RCCTE}$*; $HDRC_{RCCTE}^2$*; HEU.$HDRC_{RCCTE}$*; HEU.$HDRC_{RCCTE}^2$; HEU^2.$HDRC_{RCCTE}$*; HEU^2.$HDRC_{RCCTE}^2$*
$Model_{REH}$. Tsp.A1	MNLR	0.753	2.2	-----	7.E+00	-----	Tsp	HEU*; HEU^2*; $HDRC_{REH}$*; $HDRC_{REH}^2$*; HEU.$HDRC_{REH}$*; HEU.$HDRC_{REH}^2$*; HEU^2.$HDRC_{REH}$; HEU^2.$HDRC_{REH}^2$*
				ApproachA2				
$Model_{RCCTE}$. HEU.A2	ANN	0.972	8.4	71%	1.7.E+02	11	HEU	$HDRC_{RCCTE}$, Tsp, HA%, HG, HP, IR
$Model_{REH}$. HEU.A2	ANN	0.951	9.8	102%	2.3.E+02	15	HEU	$HDRC_{REH}$, Tsp, HA%, HG, HP, IR
$Model_{RCCTE}$. Tsp.A2	ANN	0.937	1.1	----	1.8.E+00	11	Tsp	$HDRC_{RCCTE}$, Tsp, HA%, HG, HP, IR
$Model_{REH}$. Tsp.A2	ANN	0.925	1.1	----	2.2.E+00	15	Tsp	$HDRC_{REH}$, Tsp, HA%, HG, HP, IR

Only for regression statistical models: significant at 1%: *; significant at 5%: **.

Analysing Table 31it is possible to conclude that six of the eight Portugal specific models proposed (shaded in grey) revealed to be relatively good predicting models. These are described as follows:

a) the RCCTE specific model to predict HEU using the first approach: only varying physical characteristics of the building archetypes and geographical locations ($Model_{RCCTE}$. HEU.A1, a MNLR statistical model);
b) the REH specific model to predict HEU using the first approach: only varying physical characteristics of the building archetypes and geographical locations ($Model_{REH}$. HEU.A1, a MNLR statistical model);
c) the RCCTE specific model to predict HEU using the second approach: varying physical characteristics of the building archetypes, geographical locations and

occupancy and occupant behaviour (OOB) characteristics ($Model_{RCCTE}$. HEU.A2, ANN statistical model);

d) the REH specific model to predict HEU using the second approach: varying physical characteristics of the building archetypes, geographical locations and OOB characteristics($Model_{REH}$. HEU.A2, ANN statistical model);

e) the RCCTE specific model to predict Tsp using the second approach: varying physical characteristics of the building archetypes, geographical locations and OOB characteristics ($Model_{RCCTE}$. Tsp.A2, ANN statistical model);

f) the REH specific model to predict Tsp using the second approach: varying physical characteristics of the building archetypes, geographical locations and OOB characteristics($Model_{REH}$. Tsp.A2, ANN statistical model).

In the approach A1 (see Table 25, section 5.3.1), errors resulted mainly from the differences between the heating patterns and indoor heat gains values assumed in the HEU simulations and the $HDRC_{RCCTE}$/$HDRC_{REH}$ calculations. The errors also reflect the influences of the RCCTE and REH simplified calculation methodologies and the differences in the use of certain values by default (e.g., air infiltration rate/natural ventilation) in the $HDRC_{RCCTE}$/$HDRC_{REH}$ calculations or assumed by the users.

The approach A2 (see Table 27, section 5.3.2) attempted to cope with some of the issues intrinsic to models developed under A1 by including additional independent variables (*IR, HA%, HP, HG*) to explain better the HEU. Still, like universal models, these variables fail to explain where and when spaces are being heated as the independent variables *IR, Tsp, HG* and *HA%* do not account neither with the effect of orientation of the heated spaces nor with the period of heating during the day on the heating energy use.

An in-depth analysis on the development of the six models is described next:

Concerning the RCCTE and the REH specific models to predict HEU using approach A1- **$Model_{RCCTE}$. HEU.A1** and **$Model_{REH}$. HEU.A1**, although the MLNR errors measured through MAE, MAPE and MSE are acceptably high, the R^2 exhibit satisfactory values, meaning that these models can be used to predict HEU. The $Model_{RCCTE}$. HEU.A1 predicts HEU with a R^2 of 0.84 using the variables *Tsp* and $HDRC_{RCCTE}$, and other independent variables presented in Table 31. In turn, the $Model_{REH}$. HEU.A1 predicts HEU with a R^2 of 0.779 using the variables *Tsp* and $HDRC_{REH}$, and other independent variables presented in Table 31.

All the detailed results regarding the MNLR statistical model are presented in Appendix C for $Model_{RCCTE.}$ HEU.A1 and $Model_{REH.}$ HEU.A1 (parameter estimates in Table C.13 and Table C.14; comparison between observed and predicted values, using the testing dataset, in Figure C.6 and Figure C.7, respectively).

From Table 31, it can be concluded that RCCTE and REH specific models for predicting HEU using approach A2 - **$Model_{RCCTE}$ HEU.A2** and **$Model_{REH}$ HEU.A2**, perform well, with high R^2 and a satisfactory MAE values, besides the fairly high errors for the accuracy metrics MAPE and MSE. The $Model_{RCCTE}$. HEU.A2 predicts HEU with a R^2 equal to 0.972 using the variables $HDRC_{RCCTE}$, *Tsp*, *HA%*, *HG*, *HP*, *IR*. In turn, the $Model_{REH}$. HEU.A2 predicts HEU with a R^2 of 0.951 using the variables $HDRC_{REH}$, *Tsp*, *HA%*, *HG*, *HP*, *IR*.

All the detailed results regarding the ANN statistical model are presented in Appendix C for $Model_{RCCTE.}$ HEU.A2 and $Model_{REH.}$ HEU.A2 (comparison between observed and predicted values, using the testing dataset, in Figure C.8 and Figure C.9, respectively).

Table 31 shows that the RCCTE and REH specific models for predict Tsp using approach A2 - **$Model_{RCCTE}$. Tsp.A2** and **$Model_{REH}$. Tsp.A2** - perform well in predicting Tsp, with high R^2 values and low errors. The $Model_{RCCTE}$. Tsp.A2 predicts Tsp with a R^2 of 0.937, using the variables $HDRC_{RCCTE}$, *HEU*, *HA%*, *HG*, *HP*, *IR*. In turn, the $Model_{REH}$. Tsp.A2 predicts HEU with a R^2 of 0.925, using the variables $HDRC_{REH}$, *Tsp*, *HA%*, *HG*, *HP*, *IR*.

All the detailed results regarding the ANN statistical model are presented in Appendix C for $Model_{RCCTE.}$ Tsp.A2 and $Model_{REH.}$ Tsp.A2 (comparison between observed and predicted values, using the testing dataset, in Figure C.10 and Figure C.11, respectively).

Like the universal models, the results of Tsp prediction models should be analyzed with care as the *Tsp* variable was considered as a discrete variable.

5.7 Graphical representation of the energy-temperature relationship

A graphical representation is shown in the next sections to provide insights on the relationship between the heating energy use, the indoor temperatures and heating energy demand under reference conditions (HDRC).

The graphs were developed using the models created under approach A2 (see sections 5.5.2, 5.5.3 and 5.6.2 and 5.6.3). Section 5.7.1 presents the graphs showing the heating energy use as function of set point temperature and HDRC, whereas section 5.7.2 shows the set point temperature as function of heating energy use and HDRC. The three alternative representations of HDRC values ($HDRC_{st}$, $HDRC_{RCCTE}$ and $HDRC_{REH}$) are addressed, each in a different graph. It was assumed: 37% of the area scheduled for heating (HA%) for the entire heating period (HP) with indoor heat gains of 4 W/m^2, for two scenarios of air infiltration rate/natural ventilation (IR): 0.6 and 1.0ac/h. To be noted that the low HDRC values in the scenarios assuming 1.0ac/h are only realistic in very mild climates.

5.7.1 Heating energy use as a function of indoor temperature and HDRC

The figures found in this section enable several analyses. For example, Figure 35 shows that a dwelling with a $HDRC_{st}$ of a 150 kWh/m^2.year would require approximately 80 kWh/m^2.year to achieve a minimal guaranteed indoor temperature of 20ºC if, in practice, only a 37% of the house is heated in a week. But if the indoor temperature set point was relaxed to 16ºC, then the heating required would be only about 55kWh/m^2.year.

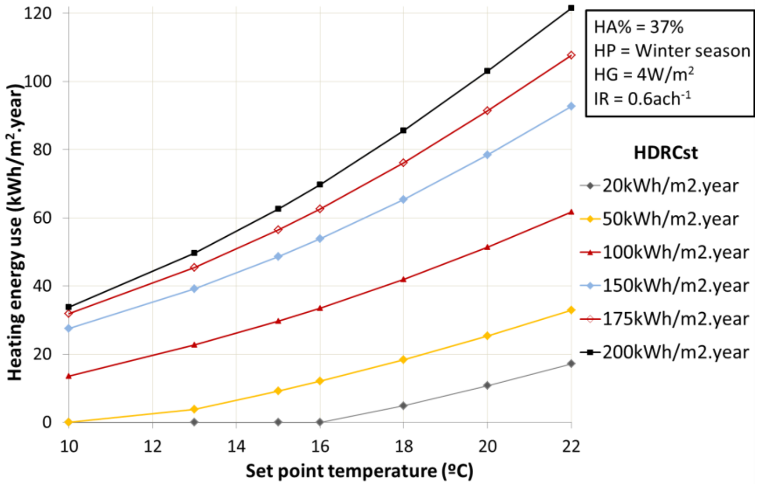

Figure 35. HEU as a function of Tsp and $HDRC_{st}$, assuming 0.6ac/h.

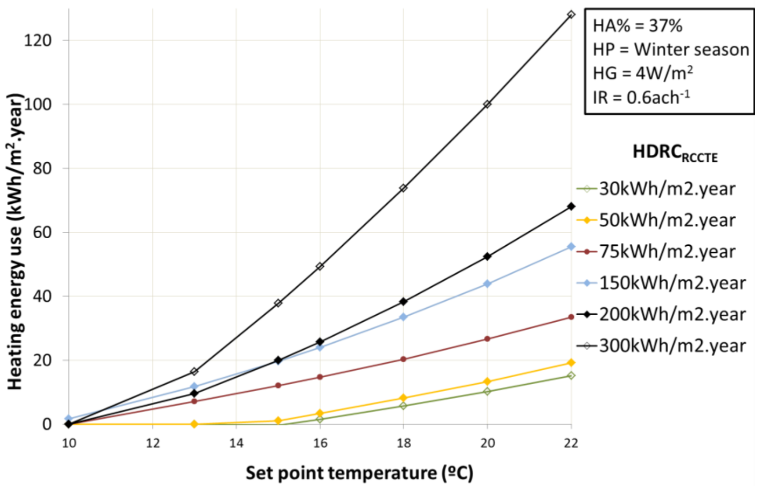

Figure 36. HEU as a function of Tsp and $HDRC_{RCCTE}$, assuming 0.6ac/h.

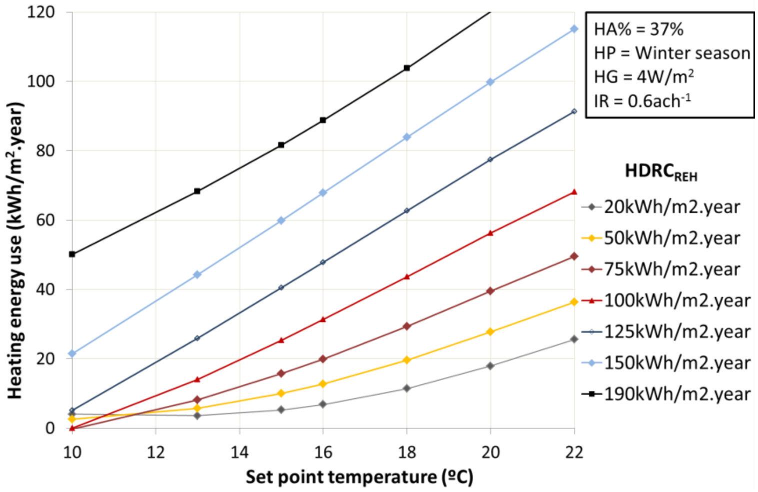

Figure 37. HEU as a function of Tsp and $HDRC_{REH}$, assuming 0.6ac/h.

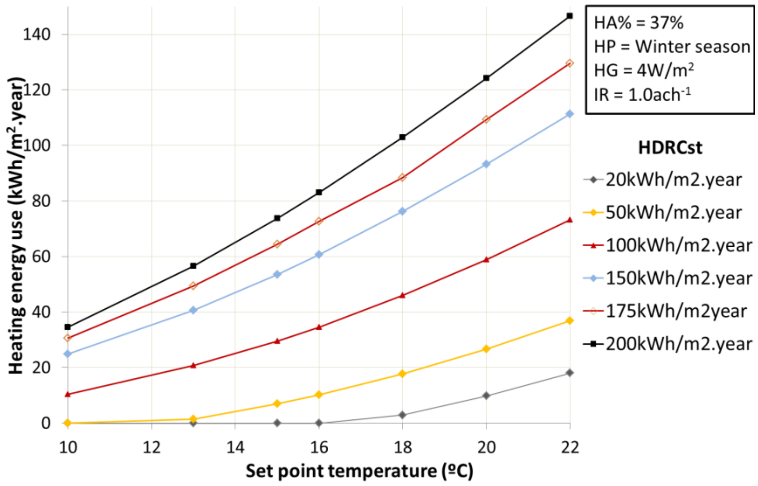

Figure 38. HEU as a function of Tsp and $HDRC_{st}$, assuming 1.0ac/h.

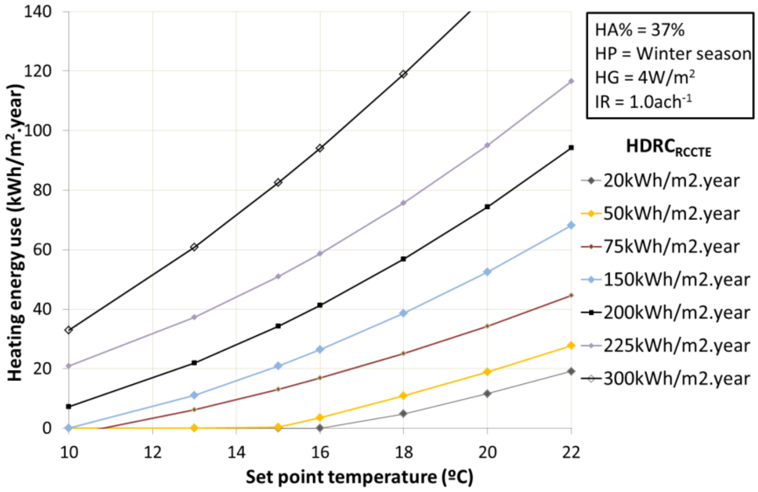

Figure 39. HEU as a function of Tsp and $HDRC_{RCCTE}$, assuming 1.0ac/h.

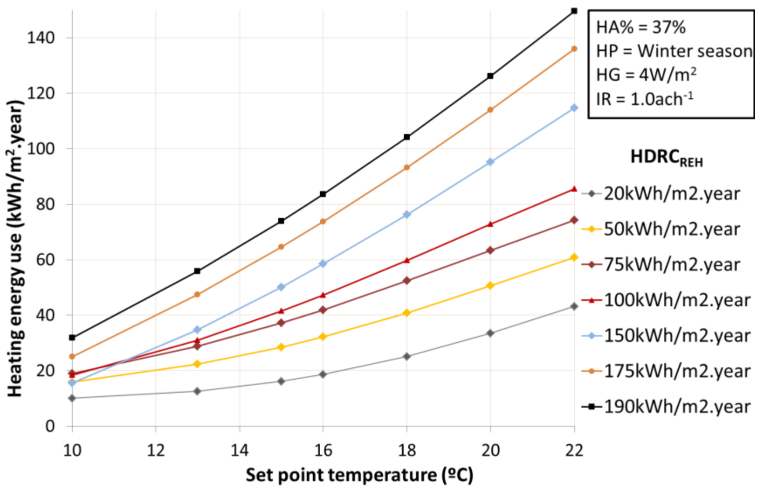

Figure 40. HEU as a function of Tsp and $HDRC_{REH}$, assuming 1.0ac/h.

5.7.2 Indoor temperature as function of heating energy use and HDRC

The figures found in this section enable several analyses. For example, Figure 41 shows that if a dwelling with a $HDRC_{st}$ of 100 kWh/m^2.yearuses approximately 30 kWh/m^2.year, the likely minimal guaranteed indoor temperature of spaces when heated is only about 16.5ºC.

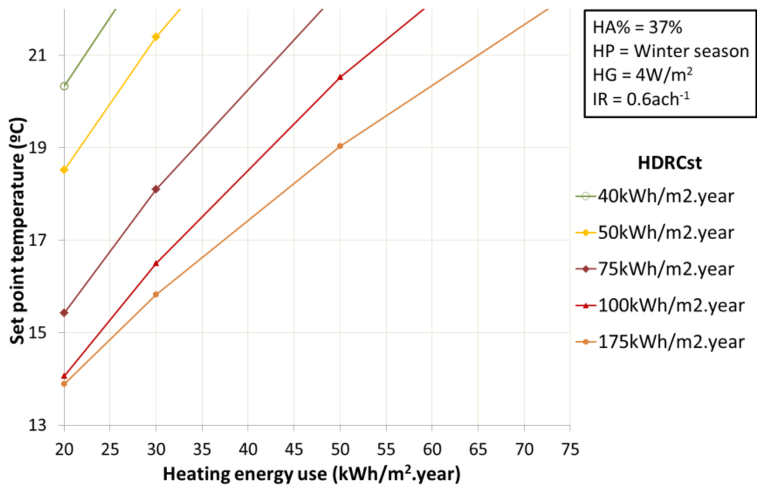

Figure 41. Tsp as function of HEU and $HDRC_{st}$, assuming 0.6ac/h.

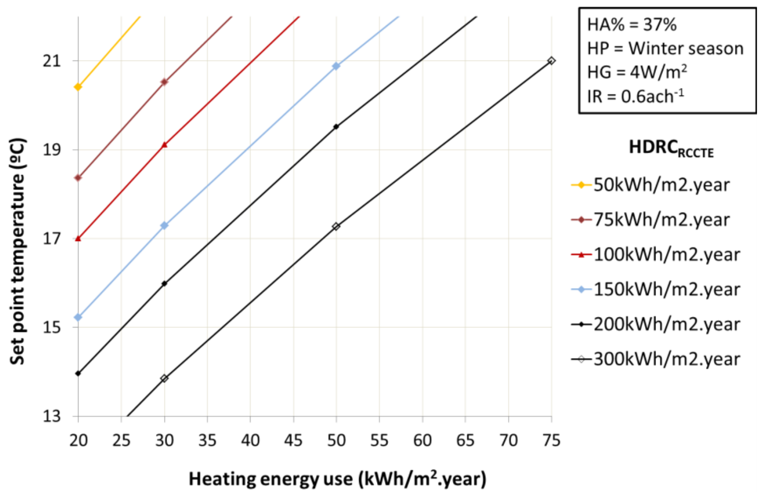

Figure 42. Tsp as function of HEU and $HDRC_{RCCTE}$, assuming 0.6ac/h.

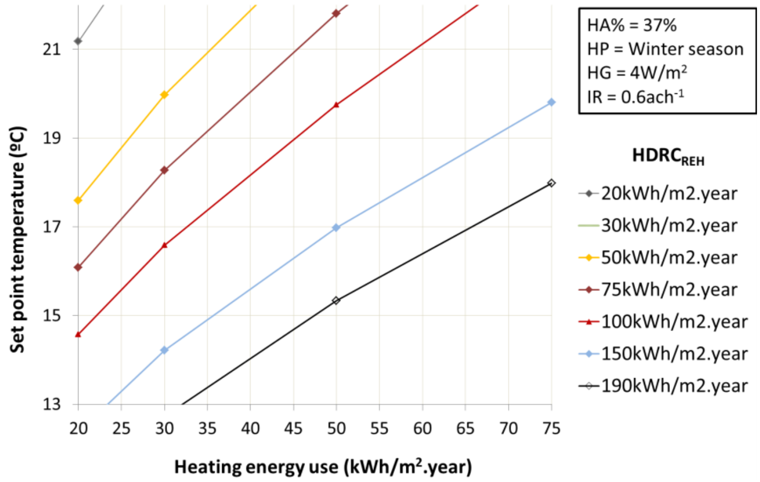

Figure 43.Tsp as function of HEU and $HDRC_{REH}$, assuming 0.6ac/h.

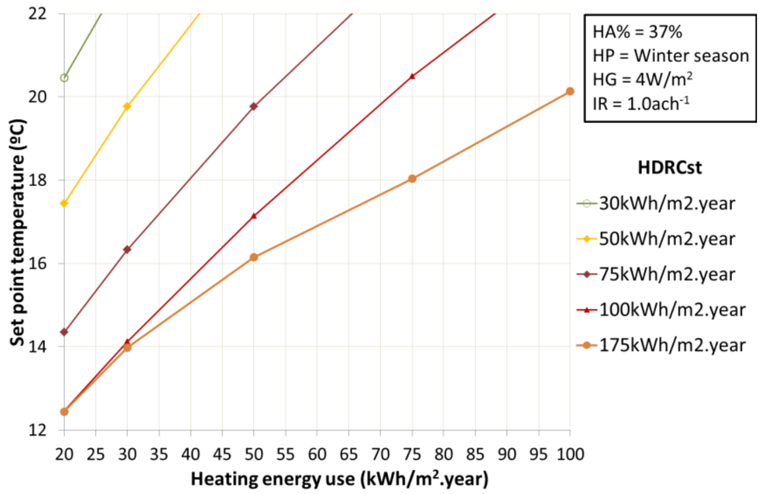

Figure 44. Tsp as function of HEU and $HDRC_{st}$, assuming 1.0ac/h.

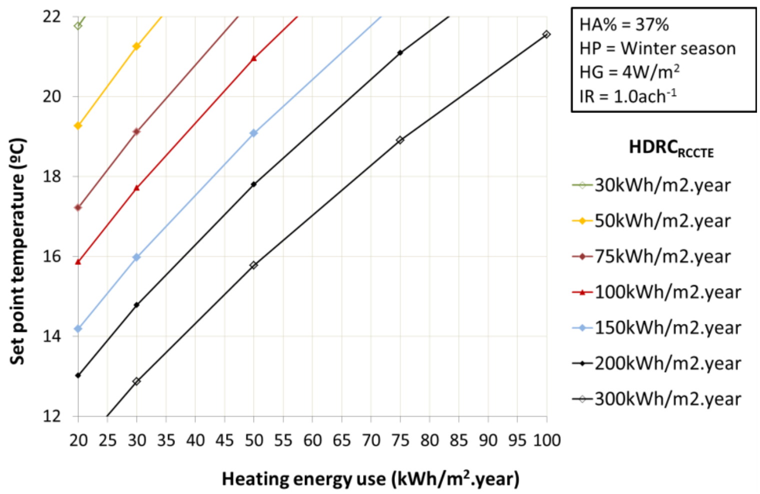

Figure 45. Tsp as function of HEU and $HDRC_{RCCTE}$, assuming 1.0ac/h.

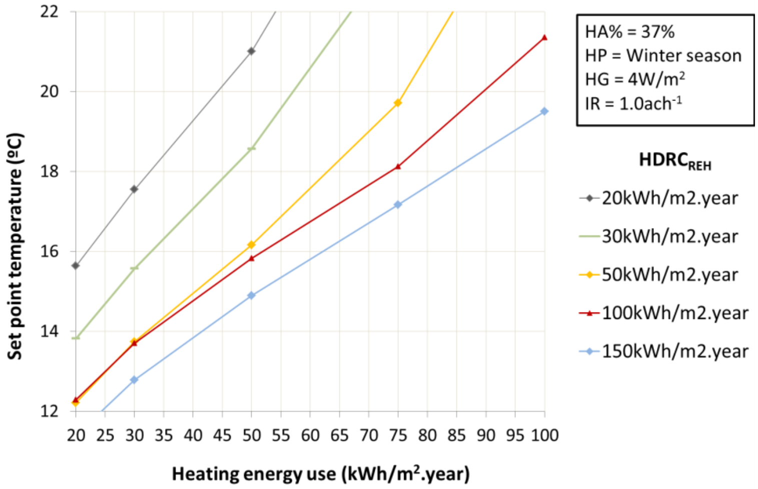

Figure 46. Tsp as function of HEU and $HDRC_{REH}$, assuming 1.0ac/h.

5.8 Estimation of the 'heating gap'

The 'heating gap' aims to indicate, indirectly, the existence of thermal comfort deficit in the residential building stock during heating season. It is also likely a significant indicator of the potential for rebound effect and trend for future energy demand for heating.

It was possible to estimate more accurately the 'heating gap' using the predicting models developed in this chapter.

'Heating gap' was estimated in two main steps. First, a more relaxed value of theoretical heating energy demand of the entire residential building stock, under thermal comfort conditions (THD_{rtcc}) (*(2)* in Figure 1 in section 1.2), was computed using the RCCTE specific model developed applying an ANN statistical model under section 5.6 ($Model_{RCCTE}$. HEU.A2) to predict HEU. The discrete values of each independent variable considered in the predicting model are presented in Table 32.

Table 32. Inputs to the predicting model.

HEU predicting model independent variables	Discrete values	Source
$HDRC_{RCCTE}$	150 kWh/m^2.year	Estimated based on section 3.4.
Tsp	19ºC	Based on Table 16, section 4.2.3; section 4.1.3; and ref [214].
HA%	37%	Based on section 4.1.3; Table 17 in section 4.2.4; Table B.1, Appendix B; and ref [214].
HG	4 W/m^2	Based on ref [72,73].
HP	December to February (6)	Based on Table 9, in section 4.1.3.
IR	1.0ac/h	Based on Table C.15 in Appendix C and ref [214].

The theoretical heating energy demand under RCCTE reference conditions ($HDRC_{RCCTE}$) was estimated by dividing the corresponding value in terms of GWh/year (80313 GWh/year), for the entire Portuguese residential building stock (calculated in section 3.4), with the total built area, giving an average value of 150 kWh/m^2.year.

The discrete values of the remaining independent variables were assumed based on the results obtained from the monitoring campaign analyzed under chapter 4. Those are detailed next:

1. For the percentage scheduled area (HA%): the majority of the households (48%) would prefer to have heated living room, kitchens, bathrooms and bedrooms (just 33% of the households confirmed that have heated all those areas) (section 4.1.3). Furthermore, 46% admitted that they would prefer to have heated for longer periods during the day (section 4.1.3). Note that a large portion heats only during the evening and other considerable portion does not heat at all (Table 17, section 4.2.4). For these reasons, assuming a pattern (see Figure C.12 to Figure C.14, in Appendix C) that reflects heating a dwelling with 116m^2 accordingly with the occupation pattern (49% of the households referred being only at home in the evening, see Table B.1, Appendix B), a value of 37% was proposed to accommodate these needs. The value of 116m^2 is the average floor

area of the usual residential buildings in the Northern[14] Portugal estimated from Census 2011, INE [214];

2. For the set point temperature (Tsp): the estimated mean indoor neutral temperature during the occupied period in the monitored locations in the Northern Portugal was around 18ºC (Table 16, section 4.2.3). In fact, this value would be higher if considering warmest locations. Also, it was concluded that the majority of the households would like their homes to be little warmer, and in some cases, much warmer (see section 4.1.3). Therefore, it was thought that 20ºC would be a good compromise for the all country; Finally, considering more relaxed temperature in the bedrooms during sleeping periods of 16ºC [52], it was estimated a weekly weighted average value temperature of 19ºC, assuming a dwelling with the average floor area of 116m^2 (see the heating patterns presented in Figure C.12 to Figure C.14, in Appendix C);
3. For the indoor heat gains (HG): It was assumed a value of 4 W/m^2, value that is considered in RCCTE and REH regulations [72,73];
4. For the heating period (HP): the majority of the monitored homes heated the bedroom during 0 to 1 month, and a high share of households heated the living rooms during 4 to 5 months (Table 9, in section 4.1.3). 71% of the households would prefer to have heated for longer periods during the winter season. Considering these results, and that southern regions of Portugal require a shorter period for heating, the period between December and February was selected as an average Portuguese heating pattern;
5. For the air infiltration rate/natural ventilation (IR): considering the assumed air infiltration rate values, for each type of building, and the number of apartments (51%) and houses (49%), from the total number of residential buildings in Portugal mainland (data from Census 2011, INE [214]), (see Table C.15 in Appendix C), it was possible to propose a weighted average air infiltration rate of 1.0ac/h.

The HEU predicting model estimated a 'THD_{rtcc}' value of 15 kWh/m^2.year, for the residential building stock. Calculating back the correspondent value in terms of GWh/year, the outcome is 8007 GWh/year.

[14] The only data available.

The next step is to compute the 'heating gap' applying the value of 'THDrtcc' (*(2)* in Figure 1 in section 1.2) and the value of 'actual energy use' (*(3)* in Figure 1 in section 1.2) estimated for space heating for the year of 2010, under chapter 3 (Table 6, section 3.5.2), into Eq. 5.16. The values used are shown in Table 33.

$$Heating\ gap = \frac{THD_{r.t.c.c.} - AEU}{THD_{r.t.c.c.}} \times 100 \quad [\%] \qquad \text{Eq. 5.16}$$

where $THD_{r.t.c.c.}$ is the theoretical heating energy demand under relaxed thermal comfort conditions (GWh/year) and *AEU* is the actual energy use (GWh/year).

Table 33. Values used in the estimation of the 'heating gap' considering new value for 'theoretical energy demand under thermal comfort conditions.

	Values used for 'heating gap' estimation	Source
Theoretical energy demand	8007 GWh/year	HEU predicting model (in this section)
Actual energy use	3632 GWh/year	Table 6, section 3.5.2

The 'heating gap' was calculated as 55% for the year of 2010, which is 40% p.p. less than the estimated 'reference heating gap' (95%) (in chapter 3). The estimated 'heating gap' value means that approximately just 45% of energy for space heating is actually being used when compared to the energy level required for thermal comfort.

This outcome is in line with the monitored low indoor temperatures presented in chapter 4. Nevertheless, it can be argued that it is still very high.

5.9 Conclusions

This chapter developed models to predict heating energy use or minimal guaranteed indoor temperature in spaces when heated both at individual and residential building stock level. 'Heating gap' was also assessed for the residential building stock in Portugal mainland.

Overall, this chapter concludes that, using the models developed under this chapter, the energy rating/certification's databases, such as the EPBD-derived EPC databases, can be relevant in the estimation of heating energy use (HEU) or of the indoor temperature, applicable both at individual and residential building stock levels. Furthermore, knowing the relationship between *heating energy use*, occupant behavior (e.g. *indoor temperatures)* and *HDRC,* heating energy use or indoor temperatures values can be estimated for different levels of occupant behaviour.

From the analysis performed, it is possible to conclude that three universal models and six Portugal specific models revealed to be robust:

1. the universal models to predict HEU using the database from varying physical characteristics of the building archetypes and geographical locations (MNLR statistical models: $R^2 = 0.93$);
2. the two universal models to predict HEU or indoor temperature using the database from varying physical characteristics of the building archetypes, geographical locations, and occupancy and occupant behaviour (OOB) characteristics (ANN statistical models: $R^2 = 0.99$ and $R^2 = 0.97$ for HEU and indoor predicting models, respectively);
3. the RCCTE and the REH specific models to predict HEU using the database from varying physical characteristics of the building archetypes, and geographical locations (MNLR statistical models: $R^2 = 0.84$ for the RCCTE specific model and $R^2 = 0.95$ for the REH specific model);
4. the RCCTE and the REH specific models to predict HEU or indoor temperature using the database from varying physical characteristics of the building archetypes, geographical locations, and OOB characteristics (ANN statistical models: $R^2 = 0.97$ and $R^2 = 0.94$ for the HEU and indoor RCCTE predicting models, respectively, and $R^2 = 0.95$ and $R^2 = 0.92$ for the HEU and indoor REH predicting models, respectively).

Predicting models using a database that results from varying only the physical characteristics of the building archetypes and geographical locations are limited in their applicability, and because they included few independent variables that explain the model (R^2 >0.78). However, the model output values can be directly obtained through regression models. Predicting models using a database that results from varying physical characteristics of the building archetypes, geographical locations and OOB characteristics required a more sophisticated technique, the ANN statistical model. This statistical method performed well on the development of the models ($R^2 > 0.93$) but it requires a high level of expertise and knowledge in the area of statistical modeling. Furthermore, the ANN models were successfully developed by applying a higher number of independent variables: *Tsp, HDRC, percentage heated area (HA%), indoor heat gains (HG), heating period (HP)* and *air infiltration rate/natural ventilation (IR)* for the HEU predicting models; and *HEU, HDRC, HA%, HG, HP* and *IR* for the Tsp predicting models.

The assessment of the 'heating gap' value was performed using the new and relaxed value of ´theoretical heating energy demand under thermal comfort conditions' estimated from a RCCTE specific model developed in this chapter. The value was computed as 55% for the year of 2010, which is 40% p.p. lower than the 'reference heating gap' values (95%) estimated under chapter 3. This value, which one can argue still being very high, means that approximately 45% of energy for space heating is actually being used when compared to the energy level required for thermal comfort. Yet, although more relaxed values of thermal comfort conditions were considered, it is recognized that the assumptions taken either for the relaxed heating patterns necessary for thermal comfort (which are difficult to acknowledge, due to its complex nature) or in the simplification behind the use of HDRC values as proxy variables (i.e., differences between parameters assumed as reference values and the actual values), into the predicting model, are associated to some degree of error. Actually, the first even faces the problematic of comfort expectation changing over time. Therefore, it is advisable to consider the estimated value of 'heating gap' with care as an indicative value.

CHAPTER 6

OVERALL CONCLUSIONS AND FUTURE WORK

This research developed models that characterize the relationship between heating energy use, indoor temperatures and the theoretical heating energy demand under reference conditions (HDRC). Both types of models are applicable to different geographical contexts (designated as universal models) and to the Portuguese context (designated as Portugal specific models), all applicable at levels of individual and residential building stock as a whole.

The motivation of the development of the models came firstly from the importance of assessing the existence of comfort deficits and/or energy use gaps, as they may give some indication on what to expect regarding the evolution of the energy use for heating and influence the design of energy plans, as well as the design of new dwellings and refurbishment of existing ones. But the reality is that the scope is much broader and comes to aid, in a user-friendly way, the estimation of heating energy use or indoor temperatures, in the residential buildings, with a greater degree of freedom in terms of assumptions for the occupant behaviour (i.e., operating conditions).

Other relevant purposes of this thesis were the assessment of the energy use gap (one variant of 'reference heating gap' and other of 'heating gap') and the characterization of current indoor temperatures for the Portuguese context, driven by the hypothesis that there could be occupants living in dwellings in Portugal that are subjected to poor indoor environment conditions during the winter season. The characterization of indoor temperatures was also used to assist checking, indirectly, the existence of an energy use gap found.

This chapter summarizes the results and conclusions of this research, which were presented and discussed in detail throughout previous chapters. It is organized as follows: section 6.1 indicates the main research contributions and section 6.2 presents their implications for real practice. Section 6.3 gives suggestions for future topics of research.

6.1 Contributions

This thesis has important contributions in the development of energy planning practices regarding the residential building stock. Also, the results of this thesis exhibit potential in using energy rating/certification schemes´ databases as a rich source of data for countries´ decision-making and future energy planning, helping to overcome the lack of data at the building level. The specific contributions offered throughout the thesis are described below.

On the methodological level, this thesis contributes with:

a) models that can be used to predict actual bedroom or living rooms indoor temperatures in the residential buildings in Northern Portugal, as function of physical (i.e., building characteristics), climatic and socio-economic inputs;
b) the advance of real world practices by developing statistical models to predict heating energy use or indoor temperatures for different levels of occupant behaviour, by taking advantage of HDRC values from energy rating/certification´s databases, such as EPBD-derived EPC databases;
c) A methodology for the assessment of the 'heating gap' and the 'reference heating gap'

Along the thesis, there were also contributions of important pieces of information, the main ones being:

a) a thorough characterization of thermal performance of the residential building stock in Portugal mainland using the Portuguese EPBD-derived EPC database;
b) a detailed characterization of actual indoor temperatures and heating patterns in the residential buildings in Northern Portugal;

c) the identification and quantification of the impact of socio-economic factors, building characteristics and climatic conditions on indoor temperatures in the residential buildings in Northern Portugal;
d) an assessment of the 'heating gap' of the residential building stock in Portugal mainland, using the predicting models and the Portuguese EPBD-derived EPC database.

From the thermal performance characterization analysis performed in chapter 3 it was possible to observe that the thermal performance of residential buildings in Portugal mainland improved in a progressive way with time. Energy regulations (as that after 2006 [72]) are pointed out as one of the main reasons, among others. Nevertheless, show about 80% of the building stock has theoretical HDRC values higher than 100kWh/m^2.year, even in a 'mild climate'.

In addition, the assessment of the 'reference heating gap' revealed a value of 95% for space heating in 2010. It must however be recognized that the differences between 'actual use' and 'theoretical energy demand' are probably, to some extent, associated with the difference between reference conditions and reality, especially in what regards the heating patterns. In particular, and giving attention to the generalized Portuguese cultural aspect of not valuing thermal comfort, reference conditions are likely a stringent excessive standard in terms of thermal comfort requirements.

The results of the monitoring campaign analyzed in chapter 4 show that, in fact, the daily mean indoor temperatures were much lower than the reference values of 18ºC assumed in the current Portuguese regulation of the thermal performance of the residential buildings [73].

The observed daily mean indoor temperatures, for the occupied period, are 15ºC for the bedrooms and 17ºC for the living rooms. Still, a wide variation in temperatures among and within locations was observed, with records of daily mean temperatures in the occupied period as low as 10ºC in sleeping rooms and in living rooms.

Actually, besides occupant´s effort on resorting to thermal adaptation strategies, 68% revealed their preference for warmer temperatures. Also, the results indicated that indoor temperatures are significantly below the levels putatively recommended by the WHO. In addition, despite some methodological issues, the results showed that indoor conditions are far from complying even with the adaptive comfort patterns. To some extent, and besides the effort of some occupants to adapt to indoor temperatures, these results came to reinforce the idea that 'cold homes' during winter season might be a reality in Portugal. This phenomenon, in turn, might have a potential negative impact on households' wellbeing and health.

It was also concluded that the models developed revealed to be very promising at predicting the actual daily mean bedroom temperature in the occupied period, and the actual living room temperatures in the occupied and 24h period, if the physical, climatic and socio-economic inputs are known. The results showed that building characteristics are the main factor (variability explained ranging from 73%-85%) affecting indoor temperatures.

A major benefit of the statistical method used (i.e., linear regression with panel corrected standard errors) is that it allows capturing information about temperature as it varies over time and across a heterogeneous building stock. It also allows combining a large number of different independent variables.

The fact that building characteristics are the main factor influencing indoor temperatures, and the evidence of what might be considered for some as low indoor temperatures, might be a good reflection of poor building construction and, at second level, of inexistency or inefficiency of heating equipment. This, along with the evidence that there are significant professional and market challenges ahead for the Portuguese construction industry (from chapter 3), emphasizes the need for properly designed buildings, in view of their local climatic conditions. This, especially in temperate climates as those of Portugal, could lead to drastically reduce final energy demand for comfort (e.g. heating) as a result of careful implementation of what is sometimes called as 'sufficiency' strategies [2–4].

From the analysis performed in chapter 5 it was possible to conclude that the models developed proved to be robust in predicting heating energy use or indoor temperatures both at an individual and at a building stock level.

The universal models applicability goes beyond any geographical contexts. Also, the fact that the employment of these models needs the conversion of the HDRC values issued in the building energy performance certificates (or calculated under its scheme or any other methodologies used to calculate HDRC) to the standard $HDRC_{st}$ values (see section 5.5.1) is an assurance that the models developed can still be used in case the energy calculation methodologies of the energy rating/certification schemes change over time.

The applicability of the specific models is direct in the Portuguese context, where HEU or indoor temperatures can be predicted applying the HDRC values (designated as the $HDRC_{RCCTE}$ or $HDRC_{REH}$, depending whether the HDRC value comes from RCCTE or REH), which are read directly in the energy building certificates.

Some limitations inherent to the modeling architecture were pointed out in chapter 5, such as the use of the variables percentage of heated area (HA%), indoor heat gains (HG), air infiltration rates/natural ventilation (IR) and set point temperatures (Tsp), and the use of HDRC variable as a *proxy* one. Yet, the practical convenience of using the HDRC values lies on the fact that the energy rating/certifications´ databases, such as the EPBD-derived EPC databases, hold a great number of different certificates, making it a repository of HDRC dataset. Also HDRC results from a reasonably detailed evaluation of the buildings/dwellings.

Furthermore, the modeling of heating energy use or indoor temperatures took the advantage of being developed using statistical models. The preference for statistical models coupled with simulation or calculations data makes possible to predict outputs from the models without needing to resort to building simulation software. Thus, statistical models allow one to reduce significantly the computation time.

In addition, the modeling architecture (it includes variables representing occupant behaviour) of the statistical models developed allow the estimation of heating energy use or indoor temperatures values for different levels of occupant behaviour.

In summary, the models developed can be applied to perform fast estimations when no better information on building data and climate is available.

The fact that, some occupants revealed their preference for warmer indoor temperatures (in section 4.1.3) might corroborate the existence of an energy use gap for the residential buildings in Portugal mainland. An assessment of the 'heating gap', as defined in section 1.2, was performed using a RCCTE specific model developed in chapter 5 to predict heating energy use. It was concluded that the 'heating gap' was 55%, meaning that approximately only 45% of energy for space heating is actually being used when compared to the energy level required for thermal comfort, even under relaxed patterns. This gap can potentially mean implications on future energy demand, if there is an unfulfilled 'deficit of thermal comfort' conditions.

6.2 Implications for the real practice

The characterization of the thermal performance of the Portugal mainland residential building stock as well as the impact of regulations on its evolution, performed in chapter 3, provide relevant insights to the processes of energy planning of a country or region.

Specific implications for the real practice of the results from chapter 4 are the insights on current indoor temperatures and heating patterns, enabling more accurate estimations of energy (e.g. actual energy use and/or energy savings predictions in the residential building stock, allowing to consider rebound effects). These insights, along with the models developed, can similarly have important implications for policymakers in the establishment and development of programmes to improve indoor thermal comfort and health conditions.

Apart from the use of the models developed in chapter 5 to predict heating energy use or indoor temperatures, overall, their great implication for real practice is the fact that models can play a significant role in decision-making and future energy planning [256].

6.3 Future work

It is recognized that there is still space for the improvement of the 'heating gap' quantification method. It is important to highlight the need of further research on thermal comfort expectations at a national level. Of particular interest, it would be important to better understand how thermal comfort expectations vary with age, building/equipment upgrades and other factors. With this more accurate information for the entire residential building stock, better assessments of 'heating gap', using the models developed under this thesis, could be performed (e.g., by regions).

It would be also interesting to extend the methodology proposed to characterize the actual indoor temperatures of the residential building in Northern Portugal (chapter 4) on other regions of the country, promoting the design of energy policies for the entire national context.

In addition, it would be interesting to extend the methodology developed in chapter 4 in order to quantify the impact of different heating patterns (e.g., length of heating period during the day) on indoor temperatures.

The heating energy use or indoor temperatures models presented in chapter 5 were developed aiming to be simple in use. The limitations behind the development of the models are in part derived from this simplicity. Still, these limitations suggest possible improvements to the models that would result on more accurate but more complex ones. In an initial stage, further analyses on the impact of the variables (*HA%*, *HG*, *IR* and *Tsp* variables) that don't reflect entirely the effect of orientation and heating period during the day on heating energy use is suggested in order to understand if the impact is significant enough to raise the need for improvements. For example, simulations, for a specific value of HA%, considering different heating patterns that would vary with orientation and heating period (e.g., HA% of 20%, where most of the area, oriented towards the South, is heated during the evening, and a HA% of 20%, where most of the area, oriented towards the North, is heated in the morning) should be carried out and compared with each other. It would also be interesting to check how well the models work within their boundaries so that the database used in the statistical models would be improved.

Moreover, using the models developed in chapter 5, it should be interesting to investigate the impact of occupant heating behaviour on heating energy use or indoor temperatures, and to perform energy demand predictions and evaluations of different energy efficiency measures in the residential sector [60].

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Appendix A

t – index of the age fraction slot [t:1→13];

r – index of the number of sleeping rooms [r:1→8];

w, v – range of HDRC values (kWh/m^2.year) [r:1→9];

x, y – range of Energy class of certificates [r:1→9];

n (t,r) – number of certificates for fractions from age fraction slot *t* with *r* rooms;

A (t) – area (m^2) of all fractions from age fraction slot *t*;

Ā (t, r) – average area (m^2) of fractions from age fraction slot *t* with *r* rooms;

Ā (t) – average area (m^2) of all fractions from age fraction slot *t;*

HDRC (t, r) – total heating energy demand (kWh/m^2.year) of fractions from age fraction slot *t with r rooms;*

$\bar{HDRC}$ (t,r) – average heating energy demand (kWh/m^2.year) of fractions from age fraction slot *t* with *r* rooms;

$sa_v^w(t)$ – share of area built of fractions from age fraction slot *t* with HDRC (*t*) value between *v* and *w*;

$sn_v^w(t)$ – share of no. of certificates from age fraction slot *t* with Energy class between *v* and *w.*

For **Figure 6** to **Figure 9**:

$$\bar{HDRC}_{(t,r)} = \frac{\sum_{j=1}^{n(t,r)} (HDRC_{(t,r)j})}{n_{(t,r)}} \qquad \text{Eq. A.1}$$

For **Figure 10** and **Figure 12** to **Figure 14**:

$$\bar{A}_{(t)} = \frac{\sum_{j=1}^{n(t)} (A_{(t)j})}{n_{(t)}}$$ Eq. A.2

$$sa_v^w(t) = \sum_{j=1}^{n(t)} (\bar{A}_{(t)j})$$ Eq. A.3

For **Figure 15**:

$$\bar{A}_{(t,r)} = \frac{\sum_{j=1}^{n(t,r)} (A_{(t,r)j})}{n_{(t,r)}}$$ Eq. A.4

Appendix B

Detailed survey

Tabela 1. Dados pessoais das pessoas que vivem com o aluno

Para cada pessoa que vive em tua casa, responde às seguintes questões:														
Pessoa (avô, pai, tio, primo, etc)	**Idade**	**Habitualmente, quando é que estão em casa?** ***(para cada pessoa podes ter mais que 1 resposta, por exemplo no caso de trabalharem por turnos)***					**Situação profissional**						**Profissão** (mesmo que desempregadas)	**Escolaridade**
		Todo o dia	**Só ao final de tarde/ noite**	**Sempre, exceto de manhã**	**Sempre, exceto de tarde**	**Sempre, exceto à noite**	Estudante (E), reformado (R), incapacitado de trabalhar (I), é o próprio patrão (TP), trabalhador que trabalha para outra pessoa (TO) ou desempregado (D)							
							E	**R**	**I**	**TP**	**TO**	**D**		
Aluno														

Tabela 2. Tipo de propriedade da casa onde o aluno vive

Tipo de propriedade				**Há quantos anos a tua família habita esta casa?**		
Habitação própria		**Habitação alugada**				
A pagar prestação ao banco	*Não tem prestação a pagar*	*De Senhorio*	*Do estado ou cooperativas*	*Mais de 20*	*5 a 20*	*Menos de 5*

Tabela 3. Características gerais da habitação

Ano de construção da casa (aproximadamente)	**Tipo de casa**		**A tua casa já sofreu grandes obras?**		
	Moradia	**Prédio**	**Sim (se sim, em que ano?)**	**Não**	**Não sabe**

Tabela 4. Características gerais da habitação (continuação) ***(Existem esclarecimentos sobre esta tabela no site)***

Nº de pisos do prédio ou moradia onde vives	**Se viveres num prédio, responde a esta questão: Em que andar é que vives?**					**Quantas fachadas do teu apartamento ou moradia é que estão em contacto com o exterior?**			
	Rés-do-chão	1º andar sobre loja/garagem	1º andar sobre outra habitação	Entre andares	Último andar	**1**	**2**	**3**	**4**

Tabela 5. Dados de construção das paredes da habitação ***(Existem esclarecimentos sobre esta tabela no site)***

	Principal(is) material(is) da maioria das paredes ***(pode ser mais que 1 escolha)***					**Espessura total da maioria das paredes (em cm)**			**A parede tem caixa de ar?**	
No caso da:	**Betão**	**Tijolo simples**	**Tijolo duplo**	**Madeira**	**Pedra**	**<20**	**20- 40**	**>40**	**Sim**	**Não**
Parede exterior										
Paredes interiores										

Tabela 6. Dados de construção das paredes da habitação (continuação) ***(Existem esclarecimentos sobre esta tabela no site)***

Existe isolamento térmico nas paredes exteriores (esferovite, lã de rocha, etc)?				**Se houver, onde está o isolamento térmico nas paredes exteriores?**			
Não sei	**Não**	**Sim, até 4 cm**	**Sim, mais de 4 cm**	**Não sei**	**Na caixa de ar da parede**	**Na parte exterior da parede**	**Na parte interior da parede**

Tabela 7. Dados de construção dos pavimentos da habitação ***(Existem esclarecimentos sobre esta tabela no site)***

	Principal material dos pavimentos (não consideres o revestimento do chão: tacos de madeira, azulejo, etc)				**Existe isolamento nos pavimentos?**			
No caso do:	**Madeira**	**Pedra**	**Betão**	**Não sei**	**Não sei**	**Não**	**Sim, até 4cm**	**Sim, mais de 4 cm**
Pavimento rés-do-chão								
Outros pavimentos								

Tabela 8. Dados de construção das janelas da habitação ***(Existem esclarecimentos sobre esta tabela no site)***

	Tipo de material de caixilharia das janelas			**Tipo de vidro das janelas**		**Quando é que o sol bate nas janelas?**				**Quantas caixilharias tem cada janela?**	
No caso das janelas:	**PVC**	**Madeira**	**Alumínio**	**Simples**	**Duplo**	**De tarde**	**De manhã**	**De manhã e de tarde**	**Nunca**	**1**	**2**
No quarto do aluno											
Outras janelas											

Tabela 9. Dados de construção das janelas da habitação (continuação)

	As janelas têm estores ou portadas:			**Entrada de ar exterior pelas frinchas das janelas**		
No caso das janelas:	**Interiores**	**Exteriores**	**Não têm, só cortinas**	**Não se sente**	**Sente-se mais ou menos**	**Sente-se bastante**
No quarto do aluno						
Outras janelas						

Tabela 10. Dados de construção das janelas da habitação (continuação)

No caso das janelas da fachada:	Não existem janelas nesta fachada	Orientação das janelas								Qual é a SOMA da área das janelas por cada fachada?	As janelas são muito sombreadas por árvores, montes ou outras construções?	
		N	NE	E	SE	S	SO	O	NO		Sim	Não
da frente												
das traseiras												
do lado direito												
do lado esquerdo												

Tabela 11. Dados de construção da cobertura (telhado) da habitação

	Geometria do telhado		Existe Isolamento no telhado?			
	Inclinado	Plano	Não sei	Não	Sim, até 4cm	Sim, mais de 4 cm
Telhado						

Tabela 12. Características das portas da habitação

	Principal material de construção			Entrada de ar exterior pelas frinchas das portas?		
	Madeira	Alumínio	Outro (qual?)	Não se sente	Sente-se mais ou menos	Sente-se bastante
Porta exterior						

Tabela 13. Características de cada divisão da habitação

	Quais as divisões que:				Qual é a área da divisão? (em m^2)	Quantas horas por dia é que o sol incide no Inverno?	Quais as divisões com:		
	existem na casa	são aquecidas no Inverno	são ocupadas mais de uma hora por dia	não são ocupadas			Humidade / bolor	Pouca luz solar	Pouco arejamento
Sala de jantar									
Sala de estar									
Cozinha									
Quarto do aluno									
Quarto 2									
Quarto 3									
Quarto 4									
Quarto 5									
Casa de banho 1									
Casa de banho 2									
Casa de banho 3									
Escritório									
Sótão									
Cave									
Arrumos									
Marquise									
Outro (qual?):									

Tabela 14. Características das estruturas da habitação

	Situação atual das estruturas da habitação		
	Em bom estado	Precisa de reparação, mas não será possível em breve	Precisa de reparação e deverá ocorrer em breve
Cobertura (telhado)			
Pavimentos			
Paredes			
Janelas			

Tabela 15. Remodelações da habitação

Indica, por favor, caso tenhas conhecimento, as alterações que a casa foi sofrendo ao longo do tempo							
Colocação / melhoramento do isolamento nas paredes	Janelas isoladas	Janelas com vidro duplo	Passar de tijolo simples para atual	Passar de tijolo duplo para atual	Passar de madeira para atual	Passar de pedra para atual	Colocação / melhoramento de isolamento na cobertura

Tabela 16. Sistema de aquecimento da habitação

Divisões	Qual é o número de equipamentos por cada divisão da tua habitação?										Qual é o equipamento que mais usas em cada divisão?
	Radia-dor elétrico	Termo-ventilador	Lareira aberta	Lareira fechada	Ar condicio-nado	Radiador a água ligado a:			Sala-mandra /fogão a lenha	Não tem	
						Caldeira a gás	Caldeira a gasóleo	Caldeira a lenha			
Sala de jantar											
Sala de estar											
Cozinha											
Quarto do aluno											
Quarto 2											
Quarto 3											
Quarto 4											
Quarto 5											
Casa de banho 1											
Casa de banho 2											
Casa de banho 3											
Escritório											
Sótão											
Cave											
Outro:											

Tabela 17. Satisfação com o sistema de aquecimento da habitação

No geral, estás satisfeito/a com o sistema de aquecimento?					Achas que o teu sistema de aquecimento tem capacidade de atingir as temperaturas desejadas em casa?					Tendo termostato, tu ou alguém em tua casa regula-o à temperatura pretendida?
Muito satisfeito/a	Satisfeito/a	Nem sim nem não	Pouco satisfeito/a	Muito pouco satisfeito/a	Muito pouco	Pouco	Mais ou menos	Muito	Bastante	

Observações de respostas dadas a certas questões:

Questão / tabela	Observação

Final survey

Pergunta 1:

	Neste INVERNO, quando é que aqueceste as divisões da tua casa (MESMO QUE POR UM CURTO PERIODO de tempo)? *(podes ter mais que 1 escolha)*								Quais são os meses nos quais gostarias de ter aquecido as divisões e não aqueceste?
	Não aqueci	Outubro	Novembro	Dezembro	Janeiro	Fevereiro	Março	Abril	
Exemplo divisão				X	X				Oct., Nov. Fev.
Sala de jantar									
Sala de estar									
Cozinha									
Quarto do aluno									
Quarto 2									
Quarto 3									
Quarto 4									
Quarto 5									
Casa de banho 1									
Casa de banho 2									
Casa de banho 3									
Casa de banho 4									
Escritório									
Sótão									
Cave									
Arrumos									
Outro (qual?):									

Caso tenhas apontado NESTA PERGUNTA os meses em que gostarias de ter aquecido as divisões, responde por favor, à <u>Pergunta 2, a seguir:</u>

Pergunta 2: **Qual foi a principal razão para não teres aquecido as divisões nos meses em que tu querias?**

- Porque é muito caro aquecer como gostaria ____ ☐
- Ninguém sabe mexer no equipamento de aquecimento da casa____ ☐
- Esquecemo-nos de regular o equipamento de aquecimento para as temperaturas e período de tempo pretendido ☐
- O equipamento de aquecimento não é apto para aquecer a casa às temperaturas desejadas_________________ ☐
- Não tenho equipamento de aquecimento para aquecer a casa____ ☐
- Outra razão (qual?)____ ☐

Pergunta 3:

	Quais as divisões DO INTERIOR da tua casa que:			Quando é que aqueces OU aqueceste as divisões (MESMO QUE POR UM CURTO PERIODO de tempo)?				Gostarias de aquecer OU de ter aquecido mais horas durante o dia?	Depois de teres aquecido as divisões, em média, achas que atingiram as temperaturas confortáveis que tu querias?
	Foram, NALGUM MOMENTO, aquecidas OU que ainda estão a ser aquecidas?	Nunca foram aquecidas mas que gostarias de ter aquecido?	Nunca foram aquecidas porque não é preciso aquecê-las	Todo o dia	Quando está alguém em casa	Só a partir do final de tarde/ noite	Só durante o dia até ao início da noite		
Exemplo		X				X		X	Não/Sim
Sala de jantar									
Sala de estar									
Cozinha									
Quarto do aluno									
Quarto 2									
Quarto 3									
Quarto 4									
Quarto 5									
Casa banho 1									
Casa banho 2									
Casa banho 3									
Casa banho 4									
Escritório									
Sótão									
Cave									
Arrumos									
Marquise									
Outro:									

Pergunta 4: **qual foi a principal razão para não teres aquecido as divisões como tu gostarias? (*ver lista ao lado*) Razão:_______________**

Usa esta lista de RAZÕES para responderes às Perguntas 4, 5 e 6, caso estas se apliquem ao teu caso:

- **Razão A:** Porque é muito caro aquecer como gostaria;
- **Razão B:** Ninguém sabe mexer no equipamento de aquecimento da casa;
- **Razão C:** Esquecemo-nos de regular o equipamento e aquecimento para as temperaturas e período de tempo pretendido;
- **Razão D:** O equipamento de aquecimento não é apto para aquecer a casa às temperaturas desejadas;
- **Razão E:** Não tenho equipamento para aquecer a casa;
- **Razão F:** Outra razão (qual?).

Pergunta 5: **qual foi a principal razão para não teres aquecido as divisões mais horas durante o dia como tu querias? (*ver lista ao lado*) Razão:_______________**

Pergunta 6: **qual foi a principal razão para não teres aquecido as divisões à temperatura que tu querias? (isto é, àquela temperatura em que te sentirias confortável) (*ver lista ao lado*) Razão:_____________**

Pergunta 7: **Para ti, quais são as divisões que devem ser aquecidas?**
Exemplo: serão as salas, os quartos, a cozinha ou as casas de banho, etc?

Em primeiro lugar: ____________________
Em segundo lugar ____________________
Em terceiro lugar ____________________
Em quarto lugar ____________________

Pergunta 8: **Na hora de dormir achas que o teu quarto precisa de estar mais quente do que o resto da casa?**

____

Pergunta 9: **Os teus encarregados de educação tiveram dificuldades em pagar as contas de eletricidade, gás e outros combustíveis para aquecimento, nos últimos 12 meses?**
(escolhe Sim ou Não) ____________. Se sim, em que meses?__________________________

Pergunta 10. **Qual foi o conforto térmico em tua casa no geral (ou em média), neste INVERNO?**

Consideras que NESTE INVERNO a tua casa no geral (isto é, em média no conjunto de todas as divisões) foi:							Como preferias que fosse a tua casa NESTE INVERNO, em termos de temperatura?				
Extrema-mente fria	Muito fria	Ligeira-mente fresca	Confortável	Ligeira mente-quente	Muito quente	Extrema-mente quente	Muito mais fria	Um pouco mais fria	Como está	Um pouco mais quente	Muito mais quente

Pergunta 11: **Conforto térmico em casa NO INVERNO (continuação)**

NESTE INVERNO, o que fizeste para te adaptares à temperatura dentro de casa? *(podes ter mais que 1 resposta)*							
Nada	Visto mais roupa	Dentro da divisão vou para sítios mais quentes *(lareira, apanhar sol na janela, etc)*	Peço para ligar ou aumentar o aquecimento	Tomo bebidas quentes	Uso cobertores quando estou sentado	Uso botija de água quente	Outro (Qual?)

Pergunta 12. **Qual é o salário mensal médio líquido de toda a família que vive contigo (em euros)?**

0 a 350	351 a 750	751 a 1250	1251 a 2000	2001 a 3000	3001 a 5000	>5000

Table B.1. Sample characterization in terms of socio-economic characteristics.

		Porto	Ponte de Lima	Sabrosa	Bragança	Total
	Total N	**41**	**42**	**27**	**31**	**141**
Household size	0-2	7%	10%	0%	0%	5%
	3-4	78%	71%	81%	74%	76%
	5-6	12%	17%	15%	19%	16%
	7-8	2%	2%	4%	0%	2%
	Not answered	0%	0%	0%	6%	1%
Household	Children, adults and older people	5%	12%	4%	6%	7%
	Children and adults	58%	88%	30%	81%	67%
	Adults and older people	2%	0%	11%	0%	3%
	Adults	34%	0%	56%	3%	21%
	Not answered	0%	0%	0%	10%	2%
Monthly net income (€/month)	0-350	7%	2%	0%	0%	3%
	351-750	22%	14%	15%	0%	13%
	751-1250	20%	33%	44%	10%	26%
	1251-2000	12%	24%	22%	19%	19%
	2001-3000	5%	7%	15%	32%	13%
	3001-5000	2%	5%	4%	19%	7%
	Not answered	32%	14%	0%	19%	18%
Professional situation of the active households	No active households	2%	5%	4%	0%	3%
	All unemployed	12%	5%	4%	6%	7%
	Most unemployed	2%	0%	0%	0%	1%
	Half employed	17%	24%	15%	10%	17%
	Most employed	0%	0%	4%	0%	1%
	All employed	66%	62%	70%	71%	67%
	Not answered	0%	5%	4%	13%	5%
Minimal occupied period during the day	Always, except in the evening	2%	0.0%	0.0%	0%	1%
	Always, except in the afternoon	10%	0.0%	0.0%	3%	4%
	Always, except in the morning	2%	2.4%	0.0%	0%	1%
	Only in the evening	34%	50.0%	55.6%	61%	49%
	All day at home	51%	47.6%	44.4%	26%	43%
	Not answered	0%	0.0%	0.0%	10%	2%

Table B.2. Sample characterization in terms of building characteristics.

		Porto	Ponte de Lima	Sabrosa	Bragança	Total
	Total N	**41**	**42**	**27**	**31**	**141**
Apart./House	Apartment	90%	7%	7%	45%	40%
	House	7%	93%	93%	45%	57%
	Not answered	2%	0%	0%	10%	3%
Type of dwelling	Detached	20%	69%	70%	29%	46%
	Semi-Detached	22%	7%	19%	16%	16%
	Terrace	12%	12%	11%	29%	16%
	1 front	17%	5%	0%	0%	6%
	Not answered	29%	7%	0%	26%	16%
External wall insulation	No insulation	29%	24%	15%	13%	21%
	Until 4cm	7%	36%	33%	32%	26%
	Over 4cm	2%	7%	26%	13%	11%
	Not answered	61%	33%	26%	42%	42%
Type of glazing	Single glazing	32%	36%	11%	0%	22%
	Double glazing	41%	55%	74%	3%	57%
	Not answered	27%	10%	15%	32%	21%
No. of bedrooms	1 bedroom	10%	0%	0%	0%	3%
	2 bedrooms	12%	5%	4%	0%	6%
	3 bedrooms	22%	5%	4%	16%	12%
	4 bedrooms	22%	21%	19%	13%	19%
	5 bedrooms	7%	19%	22%	3%	13%
	6 bedrooms	0%	21%	19%	10%	12%
	7 bedrooms	0%	12%	7%	3%	6%
	>7 bedrooms	0%	10%	11%	19%	9%
	Not answered	27%	7%	15%	35%	21%
Age of construction	Until 1980	7%	7%	7%	6%	7%
	1981-1990	12%	12%	7%	3%	9%
	1991-2000	22%	29%	30%	32%	28%
	2001-2011	7%	40%	41%	45%	32%
	Not answered	51%	12%	15%	13%	24%

Table B.2. Sample characterization in terms of building characteristics (continuation).

		Porto	Ponte de Lima	Sabrosa	Bragança	Total
	Total N	**41**	**42**	**27**	**31**	**141**
Type equipment	Air conditioning	0%	2%	0%	0%	1%
	Gas boiler	0%	2%	0%	28%	7%
	Diesel boiler	0%	5%	7%	3%	4%
	Wood boiler	0%	12%	4%	9%	6%
	Open fireplace	0%	19%	19%	3%	10%
	Closed fireplace	3%	17%	15%	6%	10%
	Eletric radiator	26%	12%	15%	12%	16%
	Salamander fireplace	5%	14%	30%	0%	11%
	Thermoventilator	10%	0%	0%	0%	3%
	No equipment	10%	2%	0%	0%	4%
	Not answered	46%	14%	11%	39%	28%
Existence of central system	No	66%	39%	57%	13%	44%
	Yes	0%	39%	32%	55%	31%
	Not answered	34%	21%	11%	32%	26%
Existence of thermostat	No	22%	31%	24%	3%	21%
	Yes	44%	45%	65%	65%	53%
	Not answered	34%	24%	11%	32%	26%

Table B.3. Heated areas during monitoring campaign.

Heated areas	Absolute frequency	Total relative frequency (%)	Answered relative frequency (%)
Bathrooms	1	0.7	1.0
Kitchen	7	5.0	7.1
Kitchen, bedrooms	7	5.0	7.1
Kitchen, bedrooms, WCs	1	0.7	1.0
Bedrooms	5	3.5	5.1
Bedrooms, WCs	1	0.7	1.0
Living room	12	8.5	12.2
Living room, kitchen	2	1.4	2.0
Living room, kitchen, WCs	2	1.4	2.0
Living room, kitchen, WCs	8	5.7	8.2
Living room, kitchen, bedrooms, WCs	32	22.7	32.7
Living room, bedrooms	8	5.7	8.2
Living room, bedrooms, WCs	6	4.3	6.1
None	6	4.3	6.1
Total answers	**98**	**69.5**	**100.0**
Not answered	43	30.5	
Total	**141**	**100.0**	

Table B.4. Type of areas desired for heating.

Total of desired areas	Absolute frequency	Total relative frequency (%)	Relative frequency (%)
Kitchen	2	1.4	2.2
Kitchen, bedrooms	5	3.5	5.4
Kitchen, bedrooms, WCs	3	2.1	3.3
Bedrooms	2	1.4	2.2
Living room	5	3.5	5.4
Living room, kitchen	1	0.7	1.1
Living room, kitchen, WCs	1	0.7	1.1
Living room, kitchen, bedrooms	11	7.8	12.0
Living room, kitchen, bedrooms, WCs	45	31.9	48.9
Living room, bedrooms	11	7.8	12.0
Living room, bedrooms, WCS	5	3.5	5.4
Living room, bedrooms, kitchen	1	0.7	1.1
Total	**92**	**65**	**100.0**
Not answered	49	35	
Total	**141**	**100.0**	

Table B.5. Heating for the desired period during winter season.

	Absolute frequency	Total relative frequency (%)	Relative frequency (%)
Wanted to heat longer during winter season	27	19	29
Heated as desired	65	46	71
Total	**92**	**65**	**100**
Not answered	49	35	
Total	**141**	**100**	

Table B.6. Heating for the desired period during the day.

	Absolute frequency	Total relative frequency (%)	Relative frequency (%)
Wanted to heat longer during the day	22	16	54
Heated as desired	19	13	46
Total	**41**	**29**	**100**
Not answered	100	71	
Total	**141**	**100**	

Table B.7. Preferences for indoor temperatures in the four locations of study.

Preferences for indoor temperatures	Porto			Ponte de Lima			Sabrosa			Bragança		
	A.F.	T.R.F. (%)	R.F. (%)	A.F.	T.R.F. (%)	R.F. (%)	A.F.	T.R.F. (%)	R.F. (%)	A.F.	T.R.F. (%)	R.F. (%)
As it is	6	15%	19%	20	48%	54%	9	33%	38%	14	45%	61%
A little bit warmer	20	49%	63%	14	33%	38%	13	48%	54%	9	29%	39%
A lot warmer	6	14%	18%	3	7%	8%	2	7%	8%	0	0%	0%
Total	32	78%	**100%**	37	88%	**100%**	24	89%	**100%**	23	74%	**100%**
Not answered	9	22%		5	12%		3	11%		8	26%	
Total	**41**	**100%**		**42**	**100%**		**27**	**100%**		**31**	**100%**	

A.F. - Absolute frequency
T.R.F. – Total relative frequency
R.F. - Relative frequency

Table B.8. Hourly mean bedroom temperature distribution for 7 households and the respective heating patterns.

ID household	1	2	3	4	5	6	7
Daily mean temperature (ºC)	**14.9**	**14.1**	**14.5**	**14.0**	**15.5**	**17.0**	**19.8**
Heating period during the day (from surveys)	Not answered	No heating	No heating	No heating	17:00-24:00	17:00-24:00	21:00-8:00
Hour	Hourly mean temperature (ºC)						
1	15.1	14.4	14.7	14.2	15.7	17.7	19.7
2	15.0	14.4	14.6	14.2	15.6	17.5	19.6
3	15.0	14.3	14.6	14.1	15.5	17.3	19.5
4	14.9	14.2	14.6	14.1	15.4	17.2	19.4
5	14.9	14.2	14.5	14.0	15.3	17.0	19.3
6	14.9	14.1	14.5	13.9	15.2	16.9	19.3
7	14.9	14.0	14.6	14.0	15.1	16.8	19.7
8	14.8	14.0	14.5	14.0	15.2	16.7	20.0
9	14.8	13.9	14.4	13.8	15.2	16.5	20.0
10	14.8	13.8	14.4	13.8	15.2	16.3	20.1
11	14.7	13.8	14.4	13.7	15.2	16.2	20.1
12	14.7	13.8	14.4	13.7	15.2	16.2	20.0
13	14.7	13.8	14.5	13.6	15.4	16.4	20.0
14	14.8	13.9	14.6	13.7	15.4	16.4	20.0
15	14.8	14.0	14.6	13.7	15.4	16.3	19.9
16	14.8	13.9	14.6	13.7	15.4	16.3	19.8
17	14.8	13.8	14.5	13.8	15.4	16.6	19.6
18	14.8	13.9	14.4	13.9	15.5	16.9	19.6
19	14.8	14.1	14.4	14.0	15.8	17.3	19.8
20	14.9	14.3	14.5	14.1	15.9	17.7	19.9
21	14.9	14.4	14.6	14.1	15.9	18.2	19.9
22	15.1	14.5	14.7	14.2	15.9	18.3	19.9
23	15.3	14.5	14.7	14.2	15.9	18.2	20.0
24	15.2	14.5	14.7	14.2	15.8	17.9	19.9
Inferred heating pattern	Not identified	No heating	No heating	No heating	During evening	During evening	All day

Table B.9. Distribution of heating patterns per location of study for bedrooms and living rooms.

Heating patterns inferred	Bedrooms					Living rooms				
	Sabrosa	Bragança	Pt. Lima	Porto	Total	Sabrosa	Bragança	Pt. Lima	Porto	Total
No heating	26%	7%	40%	28%	100%	13%	0%	39%	48%	100%
All day	9%	55%	0%	36%	100%	0%	56%	0%	44%	100%
During evening	16%	25%	35%	24%	100%	25%	24%	34%	17%	100%
All night	25%	33%	0%	42%	100%	0%	25%	0%	75%	100%
Other	0%	0%	0%	0%	100%	50%	0%	50%	0%	100%
N inferred	**25**	**29**	**39**	**36**		**27**	**28**	**42**	**34**	
Non identified	**12**					**9**				

Table B.10. Results from the correlation analysis between categorical variables.

	Household	No. household	Monthly net income	Active profe.	Value comfort bed.	Value comfort liv.	Apart./ House	Age construction	Wall insu.	Wall thick.	Window frame	Window orien Bed.	Window orient. Liv.	Type equip. bed.	Type equip. liv.
Household	1	0.248	0.181	0.359	0.227	0.15	0.16	0.345	0.17	0.096	0.157	0.135	0.147	0.318	0.269
No. household	0.248	1	-0.148	0.22	0.276	0.103	0.099	-0.072	0.081	-0.001	0.189	0.168	0.099	0.236	0.228
Monthly net income	0.181	-0.148	1	0.23	0.24	0.279	0.322	0.29	0.092	0.064	0.243	0.206	0.157	0.295	0.406
Professional situation.	0.359	0.22	0.23	1	0.175	0.093	0.142	0.219	0.306	0.267	0.222	0.202	0.237	0.261	0.366
Value comfort bed.	0.227	0.276	0.24	0.175	1	N.A.	0.232	0.201	0.116	0.147	0.172	0.303	N.A	0.537	N.A
Value comfort liv.	0.15	0.103	0.279	0.093	N.A.	1	0.081	0.607	0.319	0.22	0.115	N.A.	0.215	N.A.	0.238
Apart./House	0.16	0.099	0.322	0.142	0.232	0.081	1	0.228	0.298	0.214	0.228	0.248	0.184	0.456	0.603
Age construction	0.345	-0.072	0.29	0.219	0.201	0.607	0.228	1	0.513	0.006	0.284	0.214	0.271	0.263	0.364
Wall insu.	0.17	0.081	0.092	0.306	0.116	0.319	0.298	0.513	1	0.202	0.36	0.177	0.175	0.367	0.357
Wall thick.	0.096	-0.001	0.064	0.267	0.147	0.22	0.214	0.006	0.202	1	0.243	0.221	0.195	0.427	0.363
Window frame	0.157	0.189	0.243	0.222	0.172	0.115	0.228	0.284	0.36	0.243	1	0.182	0.219	0.394	0.395
Window orien bed.	0.135	0.168	0.206	0.202	0.303	N.A.	0.248	0.214	0.177	0.221	0.182	1	NA.	0.375	N.A.
Window orient. liv.	0.147	0.099	0.157	0.237	N.A	0.215	0.184	0.271	0.175	0.195	0.219	NA.	1	N.A.	0.249
Type equip. bed.	0.318	0.236	0.295	0.261	0.537	N.A.	0.456	0.263	0.367	0.427	0.394	0.375	N.A.	1	N.A.
Type equip. liv.	0.269	0.228	0.406	0.366	N.A	0.238	0.603	0.364	0.357	0.363	0.395	N.A.	0.249	N.A.	1

N.A. – Not applicable.

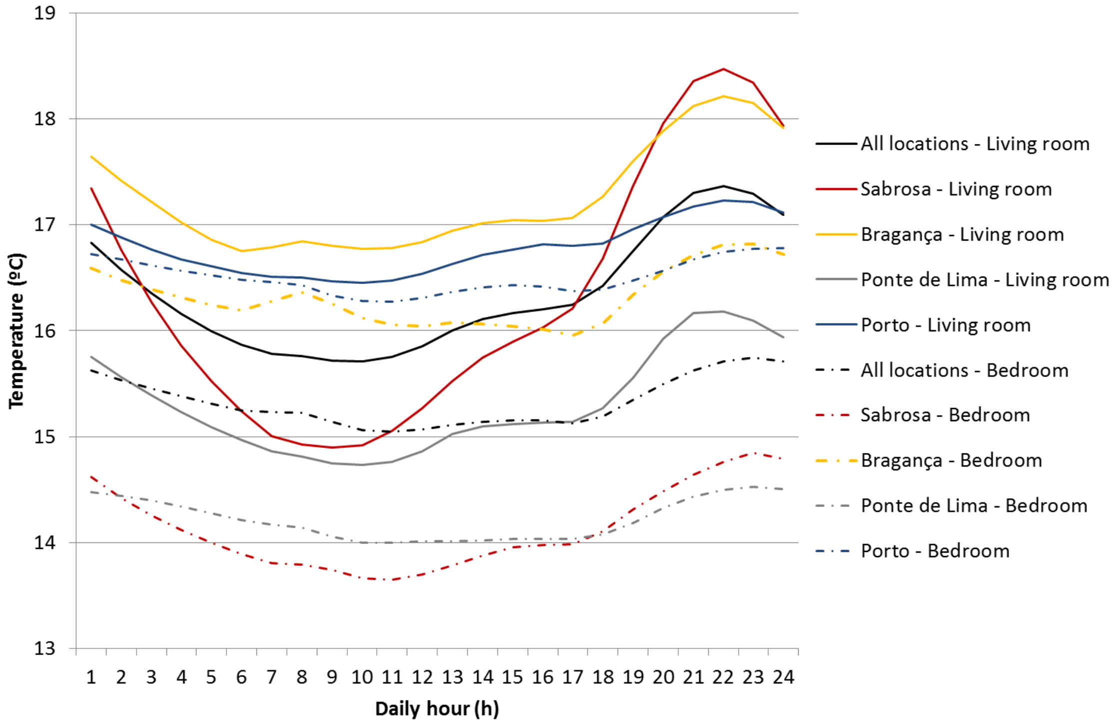

Figure B.1. Hourly mean bedroom and indoor temperatures distribution for all locations.

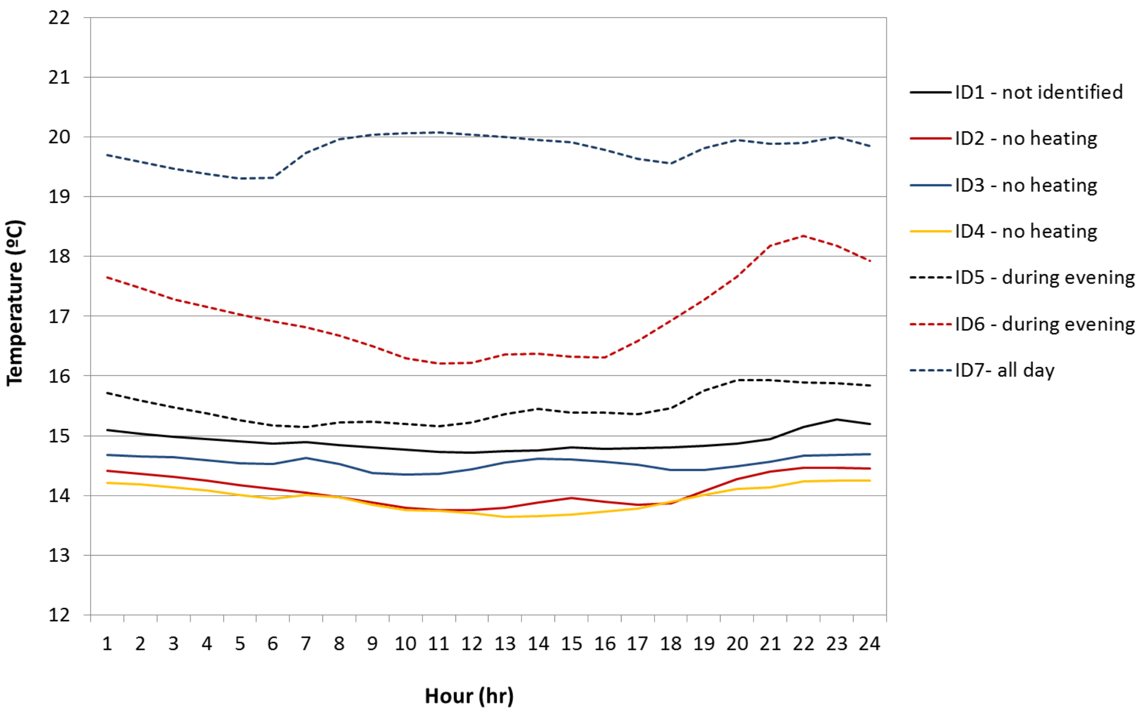

Figure B.2. Hourly mean bedroom temperature distribution for 7 households.

Appendix C

Table C.1. Details of building's structure and materials of houses used in the HEU and $HDRC_{st.}$ simulations.

Construction materials	Houses		
	<1960	1960-90	2006-14
External wall	Ordinary stone (granite, 500mm) and ordinary coated plaster (50mm each side).	Double brick wall with air cavity (110mm + 141mm + 30mm) and coated plaster (15 mm each side).	Normal brick masonry with non-traditional plaster (15 mm each side), air cavity (20mm) and EPS (60mm) between two layers of brick (110mm outside and 147mm inside).
U-values ($W/m^2.ºC$)	2.35	1.00	0.40
Windows	Simple glass (6mm), wooden window frames with shutters (25.4mm) with 40 mm air cavity between glass and shutters.	Simple glass (3mm), metal frame without thermal break, with shutters (12.7mm) and 40 mm air cavity between the glass and blinds.	PVC window frames. Double glass (exterior 6mm and interior 4mm, with 16mm of air cavity), followed by a 40mm air cavity and blinds (12.7mm).
U-values ($W/m^2.ºC$)	Uframe+glass = 5.16; Uframe+glass + Wooden shutters = 2.01	Uframe+glass = 5.70; Uframe+glass + venetian blinds = 2.85	Uframe+glass = 2.83; Uframe+glass+veneatian blind =1.88
Estimated weighted U–values* ($W/m^2.ºC$)	3.58	4.28	2.36
U-values used** ($W/m^2.ºC$)	2.89	2.92	1.90
Slab ceiling	To simulate wood ceiling, ventilated loft and pitched roof in tile: 5mm tile bedding; 43mm oak (wood).	To simulate concrete slab, ventilated attic and roof with shingles: 5mm tile bedding; 283.8 mm normal concrete; 15 mm mortar.	5mm gravel; 30mm EPS; 5mm pure asphalt; 80mm EPS; 300mm structural concrete; 10mm non-traditional plaster.
U-values ($W/m^2.ºC$)	2.50	2.80	0.32
Ground floor	300mm common earth; 300mm gravel; 200mm normal concrete; 20mm wooden floor.	300mm common earth; 300mm gravel; 200mm structural concrete; 20mm structural concrete; 20mm wooden floor.	300mm common earth; 300mm gravel; 200mm structural concrete; 40 EPS; 20mm structural concrete; 20mm wooden floor.
U-values ($W/m^2.ºC$)	0.68	0.62	0.39

Table C.1. Details of building's structure and materials of houses used in the HEU and $HDRC_{st.}$ simulations (continuation).

Construction materials	Houses		
	<1960	1960-90	2006-14
Intermediate floors	U (10 mm wood) = 4.43; U (10mm + wooden floor bars (in each 3 meters - 100mm)) = 1.33	Wooden floor (10mm) + 1st normal concrete layer (40mm) + 2nd normal concrete layer (200mm) + plaster (10mm).	Wooden floor (10mm) + 1st normal concrete layer (40mm) + 2nd normal concrete layer (200mm) + non-traditional plaster (10mm).
Estimated weighted U-values* ($W/m^2.ºC$)	4.34	--------	--------
U-values used** ($W/m^2.ºC$)	4.33	2.64	2.57
Internal Wall	Plaster (10mm) + wood (45.3mm) + plaster (10mm).	Plaster (10mm) + regular brick (130mm) + plaster (10mm).	Plaster (10mm) + regular brick (130mm) + plaster (10mm).
U-values ($W/m^2.ºC$)	2.36	1.98	1.98
Height (m)	2.70	2.64	2.60

*Assuming 50% of the time venetians are closed.

**Due to ESP-r limitations on the use of values.

Table C.2. Details of building's structure and materials of apartments for HEU and $HDRC_{st.}$ simulations.

Construction materials	Apartments		
	<1960	1960-90	2006-14
External wall	Ordinary stone (granite, 500mm) and ordinary coated plaster (50mm each side).	Double brick wall with air cavity (110mm + 141mm + 30mm) and coated plaster (15 mm each side).	Normal brick masonry with non-traditional plaster (15 mm each side), air cavity (20mm) and EPS (60mm) between two layers of brick (110mm outside and 147mm inside).
U-values ($W/m^2.ºC$)	2.35	1.00	0.40
Windows	Simple glass (6mm), wooden window frames with shutters (25.4mm) with 40 mm air cavity between glass and shutters.	Simple glass (3mm), metal frame with blinds (12.7mm) and 40mm air cavity between the glass and blinds.	PVC window frames. Double glass (exterior 6mm and interior 4mm, with 16mm of air), followed by a 40mm air cavity and blinds (12.7mm).
U-values ($W/m^2.ºC$)	Uframe+glass = 5.16; Uframe+glass + Wooden shutters = 2.01	Uframe+glass = 5.70; Uframe+glass + venetian blinds = 2.85	Uframe+glass = 2.83; Uframe+glass+veneatian blind =1.88
Estimated weighted U–values* ($W/m^2.ºC$)	3.58	4.28	2.36
U-values used** ($W/m^2.ºC$)	2.89	2.92	1.90
Intermediate floors (ceiling and the ground floor)	U (10 mm wood floor) = 4.43; U (10mm + wooden floor bars (in each 3 meters - 100mm)) = 1.33	Wooden floor (10mm) + 1st normal concrete layer (40mm) + 2nd normal concrete layer (200mm) + plaster (10mm).	Wooden floor (10mm) + 7mm EPS + 1st normal concrete layer (40mm) + 2nd normal concrete layer (200mm) + plaster (10mm).
U-values weighted estimated ($W/m^2.ºC$)	4.33	2.64	1.60
Internal walls	Plaster (10mm) + wood (45.3mm) + plaster (10mm).	Plaster (10mm) + regular brick 11 (130mm) + plaster (10mm).	Plaster (10mm) + regular brick 11 (130mm) + plaster (10mm).
U-values ($W/m^2.ºC$)	2.36	1.98	1.98
Internal walls with other occupied flats	Ordinary stone (granite, 500mm) + coated plaster (mortar ordinary 50mm each side).	Plaster (15mm) + structural concrete (120mm) + 10mm air cavity + 11 ordinary brick (110mm) + plaster (15mm).	Plaster (15mm) + 22 ordinary brick (220mm) + EPS (15mm) + plaster (15mm).
U-values ($W/m^2.ºC$)	2.35	1.29	0.824
Internal walls with non-heated areas of the building	Plaster (10mm) + wood (45.3mm) + plaster (10mm).	Plaster (15mm) + structural concrete (120mm) + 10mm air cavity + 11 ordinary brick (140mm) + plaster (15mm).	Plaster (15mm) + normal concrete (200mm) + 11 ordinary brick (110mm) EPS (37mm) + plaster (15mm).
U-values ($W/m^2.ºC$)	2.36	1.17	0.55
Height (m)	2.80	2.70	2.60

*Assuming 50% of the time venetians are closed.

**Due to ESP-r limitations on the use of values.

Table C.3. Normal solar, visible and longwave optical proprieties of glazing and venetian blinds used for each construction period for houses and apartments used in the HEU and $HDRC_{st.}$ simulations (from GSLedit´s database).

Type	<1960			1960-90			2006-14		
	R_fr	R_bk	Tran	R_fr	R_bk	Tran	R_fr	R_bk	Tran
				Normal solar optical proprieties					
Veneatian blind	0.150	0.150	0.000	0.850	0.850	0.000	0.850	0.850	0.000
External glazing	0.270	0.095	0.289	0.043	0.043	0.227	0.283	0.204	0.465
Internal glazing	N.A	N.A	N.A	N.A	N.A	N.A	0.106	0.097	0.535
				Normal visible optical proprieties					
Veneatian blind	0.070	0.070	0.600	0.000	0.000	0.000	0.070	0.070	0.600
External glazing	0.338	0.098	0.186	0.046	0.046	0.250	0.412	0.317	0.409
Internal glazing	N.A	N.A	N.A	N.A	N.A	N.A	0.102	0.087	0.685
				Normal longwave optical proprieties					
Veneation blind	0.850	0.850	0.000	0.850	0.850	0.000	0.850	0.850	0.000
External glazing	0.837	0.837	0.000	0.840	0.840	0.000	0.332	0.840	0.000
Internal glazing	N.A	N.A	N.A	N.A	N.A	N.A	0.298	0.840	0.000
Constitution of the window in GSLedit	Venetian flat 1in Dark. StopsolClassi, Glaverbel glass			Venetian blind 1/2 in flat light. SUPGRY3.LOF glass.			Venetian blind 1/2 in flat light. 1st glass is EClAdvGold6, Pilkgto glass, North America and the 2nd is Sunergyyclear4, Glaverbel glass.		

N.A. – not applicable.

For glazing [267]**:**

R_fr: front reflectance;

R_br: back reflectance;

Tran: transmittance.

For venetian blind [267]**:**

R_fr: slat top reflectance;

R_br: slat bottom reflectance;

Tran: slat transmittance.

Table C.4. Estimated values of linear thermal bridges and values of the equivalent thermal conductivity coefficient ($U_{eq.}$) for external facades for houses used in the HEU and $HDRC_{st}$ simulations.

	Detached house									Semi-Detached house	Terrace house
Construction period	<60	60-90	06-14	06-14	06-14	<60	<60	<60	<60	06-14	06-14
Floor area (m^2)	150	150	150	350	251	225	300	150	150	150	150
No. of floors	2	2	2	2	2	3	4	2	2	2	2
% of glazing area in each facade	10%	10%	10%	10%	10%	10%	10%	75%	43%	10%	10%
Pillars / beams U-values ($W/m^2.ºC$)*	N.A	1.91	0.48	0.48	0.48	N.A	N.A	N.A	N.A	0.48	0.48
$\Sigma_{linear\ thermal\ bridges}$ (facade 1) (W/ºC)	22.2	22.1	15.3	22.6	19.3	32.6	42.9	29.3	26.9	15.3	15.3
$U_{eq.}$ (facade 1) ($W/m^2.ºC$)	2.97	1.77	0.86	0.85	0.85	2.95	2.94	5.61	3.55	0.86	0.86
$\Sigma_{linear\ thermal\ bridges}$ (facade 2) (W/ºC)	20.5	20.5	15.3	22.6	19.3	31.2	41.6	27.2	25	15.3	15.3
$U_{eq.}$ (facade 2) ($W/m^2.ºC$)	2.90	1.68	0.84	0.83	0.83	2.90	2.90	4.96	3.40	0.84	0.84
$\Sigma_{linear\ thermal\ bridges}$ (facade 3) (W/ºC)	26.6	26.5	19.0	28.8	24.6	39.5	52.8	39.5	31.5	19.0	N.A
$U_{eq.}$ (facade 3) ($W/m^2.ºC$)	2.91	1.91	0.83	0.83	0.83	2.91	2.91	4.98	3.40	0.83	N.A
$\Sigma_{linear\ thermal\ bridges}$ (facade 4) (W/ºC)	25.8	25.7	19.0	28.8	24.6	38.8	51.4	34.6	31.6	N.A	N.A
$U_{eq.}$ (facade 4) ($W/m^2.ºC$)	2.89	1.69	0.83	0.83	0.83	2.90	2.89	4.97	3.40	N.A	N.A

N.A. – Not applicable.

*It was assumed that houses constructed before 1960 do not present columns or beams in their construction. The columns/beams´s materials were assumed to be, for the period between 1960-90, plaster (15mm) + structural concrete (281mm) + plaster (15mm). For the period between 2006-14, non-traditional plaster (15mm) +structural concrete (207mm) + EPS (60mm) + brick (70mm) + non-traditional plaster (15mm).

Table C.5. Estimated values of linear thermal bridges and values of the equivalent thermal conductivity coefficient ($U_{eq.}$) for external facades for apartments used in the HEU and $HDRC_{st}$ simulations.

	Apartment 1F									2F	3F
Construction period	<60	60-90	06-14	06-14	06-14	06-14	<60	<60	<60	06-14	06-14
Floor area (m^2)	100	100	100	100	181	141	200	100	100	100	100
No. of floors	1	1	1	1	1	1	2	1	1	1	1
% of glazing area in each facade	10%	10%	10%	10%	10%	10%	10%	75%	43%	10%	10%
Pillars / beams U-values (W/m^2.ºC)*	N.A	1.91	0.48	0.48	0.48	0.48	N.A	N.A	N.A	0.48	0.48
$\Sigma_{linear\ thermal\ bridges}$ (facade 1) (W/ºC)	19.4	19.2	3.92	7.88	13.9	10.9	38.4	25.2	23.0	3.92	7.88
U_{eq}. (facade 1) (W/m^2.ºC)	2.87	1.63	0.66	0.64	0.64	0.64	2.87	4.84	3.34	0.66	0.64
$\Sigma_{linear\ thermal\ bridges}$ (facade 2) (W/ºC)	N.A	N.A	N.A	N.A	N.A	N.A	N.A	N.A	N.A	3.92	3.92
U_{eq}. (facade 2) (W/m^2.ºC)	N.A	N.A	N.A	N.A	N.A	N.A	N.A	N.A	N.A	0.66	0.66
$\Sigma_{linear\ thermal\ bridges}$ (facade 3) (W/ºC)	N.A	N.A	N.A	N.A	N.A	N.A	N.A	N.A	N.A	N.A	3.92
U_{eq}. (facade 3) (W/m^2.ºC)	N.A	N.A	N.A	N.A	N.A	N.A	N.A	N.A	N.A	N.A	0.66
$\Sigma_{linear\ thermal\ bridges}$ (facade common area) (W/ºC)	9.06	8.96	4.17	4.17	4.17	4.17	18.1	9.06	9.06	4.17	4.17
U_{eq}. (facade comum area) (W/m^2.ºC)	2.91	1.59	0.66	0.66	0.66	0.66	2.91	2.91	2.91	0.66	0.66

N.A – not applicable.

*It was assumed that dwellings constructed before 1960 do not present columns or beams in their construction. The columns/beams´s materials were assumed to be, for the period between 1960-90, plaster (15mm) + structural concrete (281mm) + plaster (15mm). For the period between 2006-14, non-traditional plaster (15mm) +structural concrete (207mm) + EPS (60mm) + brick (70mm) + non-traditional plaster (15mm).

Table C.6. Details of building's structure and materials of houses used in the $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations.

Construction materials	Houses		
	<1960	1960-90	2006-14
External wall	Assumed values from technical reports		Assumed that technician has information
U-values (W/m^2.ºC)	2.0 (interpolated from values between 0.3 m and 0.6 m from Quadro II.2 from [212])	1.10 (Quadro II.3 from [212])	0.4
Windows	Assumed values from technical reports		
U-values (W/m^2.ºC)	3.30 (Quadro III.3 from [213])	3.8 (Quadro III.3 from [213])	2.40 (Quadro III.3 from [213])
Slab ceiling	Assumed values from technical reports		Assumed that technician has information
U-values (W/m^2.ºC)	3.8 (Quadro III from [212]))	3.4 (Quadro III from [212]))	0.32
Ground floor	N.A	N.A	N.A
Intermediate floors	N.A	N.A	N.A
Internal wall	N.A	N.A	N.A
Height (m)	2.70	2.64	2.60

N.A. – Not applicable.

Table C.7. Details of building's structure and materials of apartments used in the $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations.

Construction materials	Apartments		
	<1960	1960-90	2006-14
External wall	Assumed values from technical reports		Assumed that technician has information
U-values (W/m^2.ºC)	2.0 (interpolated from values between 0.3 m and 0.6 m from Quadro II.2 from [212])	1.10 (Quadro II.3 from [212])	0.4
Windows	Assumed values from technical reports		
U-values (W/m^2.ºC)	3.30 (Quadro III.3 from [213])	3.8 (Quadro III.3 from [213])	2.40 (Quadro III.3 from [213])
Slab ceiling	N.A	N.A	N.A
Ground floor	N.A	N.A	N.A
Intermediate floors	N.A	N.A	N.A
Internal wall*	Assumed values from technical reports		Assumed that technician has information
U-values (W/m^2.ºC)	1.97 (estimated from values of Quadro II.2 from [212], not considering the air resistance)	1.0 (estimated from values of Quadro II.3 from [212], not considering the air resistance)	0.55
Height (m)	2.80	2.70	2.60

N.A. – Not applicable.

*Just the wall in contact with the common area of the building.

Table C.8. Optical proprieties of glazing and venetian blinds assumed for each construction period for houses and apartments used in the $HDRC_{RCCTE}$ and $HDRC_{REH}$ calculations.

Construction materials	1960	1960-90	2006-14
Type of glass	Single colorless glass	Single colorless glass	Double colorless glass
Solar factor of glazing with activated solar protection (100%)	Wooden shutters: 0.09 (Quadro V.4 from [72])	Venetian blinds: 0.09 (Quadro V.4 from [72])	Venetian blinds: 0.09 (Quadro V.4 from [72])
Glazing solar factor*	0.85	0.85	0.75
Winter solar factor*	0.70	0.70	0.63

*Assumed by the calculation model depending on the type of glass.

Table C.9. Hourly sensible and latent heat gains per room from occupants (1), lighting (2) and equipment (3), for weekdays.

Metabolic activity	Type HG	Start (hr)	Stop (hr)	Sens. (W)	Latent (W)	Sens (W)	Latent (W)	Power (W)	No. occupants	Fraction of time (%)
					WC					
	1	0	7	0	0					0%
Walking/standing	1	7	8	84.7	84.7	73	73		4p	29%
	1	8	19	0	0					0%
Walking/standing	1	19	22	8.8	8.8	73	73		4p	3%
Walking/standing	1	22	23	81.8	81.8	73	73		4p	28%
	1	23	24	0	0					0%
	2	0	7	0	0					
	2	7	8	8.7	0			30		29%
	2	8	19	0	0					
	2	19	22	0.9	0			30		3%
	2	22	23	8.4	0			30		28%
	2	23	24	0	0					
	3	0	7	0	0					
	3	7	8	48	0	Data from Table C.10 (Total (W) column)				
	3	8	24	0	0					
					Living room					
	1	0	19	0	0					0%
Seated/light work	1	19	22	157.0	98.1	72	45		1p/3p	35%/61%
Seated/light work	1	22	23	49.0	30.6	72	45		4p	17%
	1	23	24	0	0					0%
	2	0	19	0	0					
	2	19	23	75	0			75		100%
	2	23	24	0	0					
	3	0	19	0	0					
	3	19	22	21	0	Data from Table C.10 (Total (W) column)				
	3	22	23	9	0					
	3	23	24	0	0					

Table C.9. Hourly sensible and latent heat gains per room from occupants (1), lighting (2) and equipment (3), for weekdays (continuation).

Metabolic activity	Type HG	Start (hr)	Stop (hr)	Sens. (W)	Latent (W)	Sens (W)	Latent (W)	Power (W)	No. occupants	Fraction of time (%)
					Bedroom 1					
Seated/light work	1	0	7	144	90	72	45		2p	100%
Walking/standing	1	7	8	45.3	45.3	73	73		2p	31%
	1	8	19	0	0					0%
Walking/standing	1	19	22	23.4	23.4	73	73		1p/1p	12%/20%
Walking/standing	1	22	23	65.7	65.7	73	73		2p	45%
Seated/light work	1	23	24	144	90	72	45		2p	100%
	2	0	7	0	0					
	2	7	8	18.6	0			60		31%
	2	8	19	0	0					
	2	19	22	12	0			60		20%
	2	22	23	27	0			60		45%
	2	23	24	0	0					
	3	0	19	0	0					
	3	19	23	1	0	Data from Table C.10 (Total (W) column)				
	3	23	24	0	0					
					Bedroom 2					
Seated,light work	1	0	7	144	90	72	45		2p	100%
Walking/standing	1	7	8	45.3	45.3	73	73		2p	31%
	1	8	19	0	0					0%
Walking/standing	1	19	22	29.2	29.2	73	73		2p	20%
Walking/standing	1	22	23	65.7	65.7	73	73		2p	45%
Seated/light work	1	23	24	144	90	72	45		2p	100%
	2	0	7	0	0					
	2	7	8	18.6	0			60		31%
	2	8	19	0	0					
	2	19	22	12	0			60		20%
	2	22	23	27	0			60		45%
	2	23	24	0	0					
	3	0	19	0	0					
	3	19	23	1	0	Data from Table C.10 (Total (W) column)				
	3	23	24	0	0					

Table C.9. Hourly sensible and latent heat gains per room from occupants, lighting and equipment, for weekdays (continuation 2).

Metabolic activity	Type HG	Start (hr)	Stop (hr)	Sens.	Latent	Sens (W)	Latent (W)	Power (W)	No. occupants	Fraction of time (%)
					Kitchen					
	1	0	7	0	0					0%
Sedentary work	1	7	8	112	112	80	80		4	35%
	1	8	19	0	0					0%
Light machine work + sedentary work	1	19	22	71	93				1p/3p	45%/11%
Sedentary work	1	22	23	16	16	80	80		4	5%
	1	23	24	0	0					0%
	2	0	7	0	0					
	2	7	8	26.3	0			75		35%
	2	8	19	0	0					
	2	19	22	75	0			75		100%
	2	22	23	3.8	0			75		5%
	2	23	24	0	0					
	3	0	7	42	0					
	3	7	8	56	0					
	3	8	19	42	0					
	3	19	22	556	0			Data from Table C.10 (Total (W) column)		
	3	22	23	44	0					
	3	23	24	42	0					
					Hall					
	1	0	7	0	0					0%
Walking/standing	1	7	8	14.6	14.6	73	73		4p	5%
	1	8	19	0	0					0%
Walking/standing	1	19	23	14.6	14.6	73	73		4p	5%
	1	23	24	0	0					0%
	2	0	7	0	0					
	2	7	8	1.5	0			30		5%
	2	8	19	0	0					
	2	19	23	1.5	0			30		5%
	2	23	24	0	0					
	3	0	24	0	0			Data from Table C.10 (Total (W) column)		

Table C.10. Equipment used in each room at different periods of the day, for weekdays.

		Equipment	W	Dissipated energy (%)	Fraction of time of use (%)	Fraction of occupation in each room (%)	Total (W)
7:00-08:00	WC	Hair dryer	300	80%	20%		48
	Kitchen	Fridge	140	30%	100%		56
		Toaster	750	10%	7%		
		Microwave	1000	3%	7%		
		Coffee machine	1200	1%	7%		
		Tea kettle	1850	5%	7%		
8:00-19:00	Kitchen	Frigorifico	140	30%	100%		42
19:00-22:00	Living room	PC	250	10%	100%	61%	21
		Laptop	50	5%	100%	61%	
		Printer	75	10%		3%	
		TV	90	5%		100%	
	Bedroom 2	Laptop	50	5%	100%	12%	1
		Laptop	50	5%	100%	20%	
	Bedroom 1	2 laptops	100	5%	100%	20%	1
	Kitchen	Fridge	140	30%	100%		556
		Oven	2500	40%	11%		
		Cooker	2500	80%	17%		
		Microwave	1000	3%	9%		
		Coffee machine	1200	1%	2%		
		Dish washer machine	1000	20%	33%		
		Exhaust fan	150	0	8%		
22:00-23:00	Living room	PC	250	10%	100%	17%	9
		Laptop	50	5%	100%	17%	
		Printer	75	10%		0%	
		TV	90	5%		100%	
	Bedroom 2	Radio	50	5%	100%	45%	1
	Bedroom 1	Radio	50	5%	100%	45%	1
	Kitchen	Fridge	140	30%	100%		44
		Microwave	1000	3%	7%		
23:00-24:00	Kitchen	Fridge	140	30%	100%		42

Table C.11. Combinations of physical characteristics of the building archetypes with the occupancy and occupant's behaviour characteristics.

No. comb.	No. building archetype	Heating schedule	Occupation patterns	Level of energy use	Household size	No. Bedrooms occupied	Heating period
1-28	1-28	W2	WTO	Normal	4	2	Winter season
29	29	EO 2	MTO	Low	2	2	Winter season
30	30	EO 2	MTO	Low	2	2	Winter season
31	31	EO 2	MTO	Low	2	2	Winter season
32-33	15-16	EA	WTO	Normal	4	2	Winter season
34-35	15-16	CA 1	WTO	Normal	4	2	Winter season
36-37	15-16	EO 1	WTO	Normal	4	2	Winter season
38-39	15-16	W2	ATH	Normal	4	2	Winter season
40-41	15-16	W2	MTO	Normal	4	2	Winter season
42-43	11-13	W2	WTO	Normal	8	2	Winter season
44-45	11-13	W2	WTO	Normal	2	2	Winter season
46	11	W2	WTO	Normal	8	6	Winter season
47	13	W2	WTO	Normal	8	4	Winter season
48-49	15-16	EO 1	MTO	Normal	4	2	Winter season
50-51	15-16	EO 2	MTO	Normal	4	2	Winter season
52-53	15-16	EO 2	MTO	High	8	2	Winter season
54-60	1; 13; 15-16; 21; 23; 28	EO 2	MTO	Low	2	2	Winter season
61-62	15-16	CA 1	WTO	High	8	2	Winter season
63-64	15-16	EO 1	MTO	Normal	4	2	December
65-66	15-16	EO 1	MTO	Normal	4	2	January
67-68	15-16	EO 1	MTO	Normal	4	2	December-Jan
69-70	15-16	EO 2	MTO	Normal	4	2	December
71-72	15-16	EO 2	MTO	Normal	4	2	January
73-74	15-16	EO 2	MTO	Normal	4	2	December-Jan
75-76	1;4	CA 1	MTO	High	8	2	Winter season
77	1	CA 1	MTO	High	8	2	December
78-79	1;4	CA 1	MTO	High	8	2	January
80	1	CA 1	MTO	High	8	2	February
81-82	1;4	CA 1	MTO	High	8	2	November-Jan
83-84	1;4	CA 1	MTO	High	8	2	December-Feb
85-86	1;4	CA 1	MTO	High	8	2	December-Jan
87-88	1;4	CA 1	MTO	High	8	2	November-Feb
89-93	1;13; 21;23;28	CA 2	MTO	High	8	2	February
94	31	CA 2	MTO	High	8	2	February
95	30	CA 2	MTO	High	8	2	February
96-97	32-34	W2	WTO	Normal	4	2	Winter season
99	33	W2	WTO	Normal	4	2	December-Feb

Table C.11. Combinations of physical characteristics of the building archetypes with the occupancy and occupant's behaviour characteristics (continuation).

No. comb.	No. building archetype	Heating schedule	Occupation patterns	Level of energy use	Household size	No. Bedrooms occupied	Heating period
100	36	W2	WTO	Normal	2	2	December
101-102	35-36	W2	WTO	Normal	2	2	December-Feb
103-104	35-36	W2	WTO	Normal	2	2	February
105-106	35-36	W2	WTO	Normal	2	2	November-Feb
107-108	35-36	W2	WTO	Normal	2	2	November-Jan
109-110	35-36	W2	WTO	Normal	2	2	Winter season
111	40	W2	ATH	Normal	4	2	Winter season
112	40	W2	ATH	Normal	4	2	February
113	40	W2	ATH	Normal	4	2	December
114	40	W2	ATH	Normal	4	2	November-Jan
115	40	W2	ATH	Normal	4	2	November-Feb
116	40	W2	ATH	Normal	4	2	December-Feb
117	21	SP	MTO	Low	2	2	Winter season
118	21	SP	MTO	Low	2	2	February
119	21	SP	MTO	Low	2	2	December
120	21	SP	MTO	Low	2	2	November-Jan
121	21	SP	MTO	Low	2	2	November-Feb
122	21	SP	MTO	Low	2	2	December-Feb
123-127	13; 32; 42-44	EA	MTO	High	2	2	Winter season
128-132	13; 32; 42-44	EA	MTO	High	2	2	February
133-137	13; 32; 42-44	EA	MTO	High	2	2	December
138-142	13; 32; 42-44	EA	MTO	High	2	2	November-Jan
143-147	13; 32; 42-44	EA	MTO	High	2	2	November-Feb
148-152	13; 32; 42-44	EA	MTO	High	2	2	December-Feb
153-157	13; 21; 32; 41; 44	EA	MTO	Low	2	2	Winter season
158-161	13; 21; 32; 44	EA	MTO	Low	2	2	February
162-165	13; 21; 32; 44	EA	MTO	Low	2	2	December
166-169	13; 21; 32; 44	EA	MTO	Low	2	2	November-Jan
170-173	13; 21; 32; 44	EA	MTO	Low	2	2	November-Feb
174-177	13; 21; 32; 44	EA	MTO	Low	2	2	December-Feb
178	39	EA	WTO	Normal	4	2	Winter season
179	39	EA	WTO	Normal	4	2	February
180	39	EA	WTO	Normal	4	2	December
181	39	EA	WTO	Normal	4	2	November-Jan
182	39	EA	WTO	Normal	4	2	November-Feb
183	39	EA	WTO	Normal	4	2	December-Feb
184	37	EO 2	MTO	High	8	2	December

Table C.11. Combinations of physical characteristics of the building archetypes with the occupancy and occupant's behaviour characteristics (continuation 2).

No. comb.	No. building archetype	Heating schedule	Occupation patterns	Level of energy use	Household size	No. Bedrooms occupied	Heating period
185	37	EO 2	MTO	High	8	2	November-Jan
186	37	EO 2	MTO	High	8	2	February
187	37	EO 2	MTO	High	8	2	December-Feb
188	37	EO 2	MTO	High	8	2	December-Feb
189	37	EO 2	MTO	High	8	2	Winter season
190	21	EO 2	MTO	Low	2	2	February
191	21	EO 2	MTO	Low	2	2	December
192	21	EO 2	MTO	Low	2	2	November-Jan
193	21	EO 2	MTO	Low	2	2	November-Feb
194	21	EO 2	MTO	Low	2	2	December-Feb
195	21	EO 2	MTO	Low	2	2	February
196-198	21; 32; 43	CA 2	MTO	High	2	2	Winter season
199-201	21; 32; 43	CA 2	MTO	High	2	2	February
202-204	21; 32; 43	CA 2	MTO	High	2	2	December
205-207	21; 32; 43	CA 2	MTO	High	2	2	November-Jan
208-210	21; 32; 43	CA 2	MTO	High	2	2	November-Feb
211-213	21; 32; 43	CA 2	MTO	High	2	2	December-Feb
214-215	32; 38	CA 2	MTO	High	8	2	December
216-217	32; 38	CA 2	MTO	High	8	2	November-Jan
218-219	32; 38	CA 2	MTO	High	8	2	February
220-221	32; 38	CA 2	MTO	High	8	2	December-Feb
222-223	32; 38	CA 2	MTO	High	8	2	December-Feb
224-225	32; 38	CA 2	MTO	High	8	2	Winter season
226-227	21; 32	CA 2	MTO	Low	2	2	Winter season
228-229	21; 32	CA 2	MTO	Low	2	2	February
230-231	21; 32	CA 2	MTO	Low	2	2	December
232-233	21; 32	CA 2	MTO	Low	2	2	November-Jan
234-235	21; 32	CA 2	MTO	Low	2	2	November-Feb
236-237	21; 32	CA 2	MTO	Low	2	2	December-Feb
238-239	13; 44	CA 3	MTO	High	2	2	Winter season
240-241	13; 44	CA 3	MTO	High	2	2	February
242-243	13; 44	CA 3	MTO	High	2	2	December
244-245	13; 44	CA 3	MTO	High	2	2	November-Jan
246-247	13; 44	CA 3	MTO	High	2	2	November-Feb
248-249	13; 44	CA 3	MTO	High	2	2	December-Feb
250-251	13; 41	CA 3	MTO	Low	2	2	Winter season
252-253	13; 41	CA 3	MTO	Low	2	2	February
254-255	13; 41	CA 3	MTO	Low	2	2	December

Table C.11. Combinations of physical characteristics of the building archetypes with the occupancy and occupant's behaviour characteristics (continuation 3).

No. comb.	No. building archetype	Heating schedule	Occupation patterns	Level of energy use	Household size	No. Bedrooms occupied	Heating period
256-257	13; 41	CA 3	MTO	Low	2	2	November-Jan
258-259	13; 41	CA 3	MTO	Low	2	2	November-Feb
260-261	13; 41	CA 3	MTO	Low	2	2	December-Feb
262	21	CA 2	MTO	v.Low	2	2	Winter season
263	21	CA 2	MTO	v.Low	2	2	February
264	21	CA 2	MTO	v.Low	2	2	December
265	21	CA 2	MTO	v.Low	2	2	November-Jan
266	21	CA 2	MTO	v.Low	2	2	November-Feb
267	21	CA 2	MTO	v.Low	2	2	December-Feb

See definitions in Table 22 in section 5.2.4.2

Table C.12. Parameter estimates of the MNLR statistical model employed in the development of the universal model to predict HEU ($Model_{uni.}$ HEU.A1), for the first approach.

Dependent Variable: HEU						
Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-26.536	1.963	-13.521	.000	-30.391	-22.681
Tsp	1.16E+00	.134	8.697	.000	.899	1.424
$Tsp^2.HDRC_{st}$	1.58E-03	6.16E-05	25.670	.000	.001	.002
$Tsp^2.HDRC_{st}^2$	-1.91E-06	2.52E-07	-7.579	.000	-2.41E-06	-1.42E-06

Table C.13. Parameter estimates of the MNLR statistical model employed in the development of the RCCTE specific model to predict HEU ($Model_{RCCTE}$. HEU.A1), for the first approach.

Dependent Variable: HEU						
Parameter	B	Std. Error	T	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-15.345	1.463	-10.487	.000	-18.219	-12.471
Tsp^2	6.37E-02	.004	15.825	.000	.056	.072
$Tsp^2.HDRC_{RCCTE}$	5.93E-04	1.35E-05	44.075	.000	.001	.001

Table C.14. Parameter estimates of the MNLR statistical model employed in the development of the REH specific model to predict HEU ($Model_{REH}$. HEU.A1), for the first approach.

Dependent Variable: HEU						
Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-14.078	1.843	-7.638	.000	-17.699	-10.458
Tsp^2	7.62E-02	.005	15.258	.000	.066	.086
$Tsp^2.HDRC_{REH}$	7.74E-04	2.420E-05	31.962	.000	.001	.001

Table C.15. Total number of residential buildings in Portugal mainland (from Census 2011) and the assumed air infiltration rates per construction period.

Construction period	Total no. buildings in Portugal mainland [214]	Assumed air infiltration rate (ac/h) values	
		Apartments	Houses
2006-11	202764	0.6	0.8
91-05	1146037	0.8	1
60-90	1820731	1	1.2
<60	649042	1.1	1.3

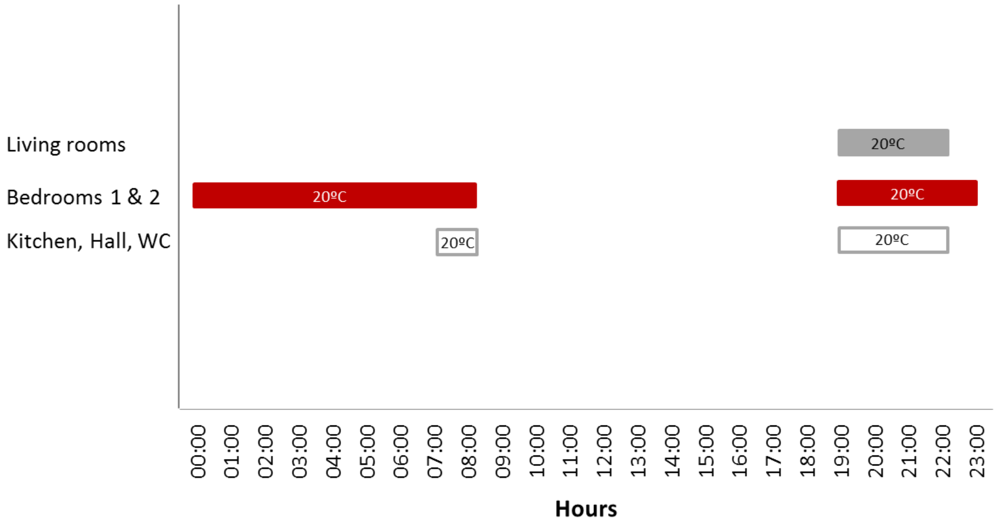

Figure C.1. Example of a heating pattern for all the rooms during weekdays for apartment 1F.

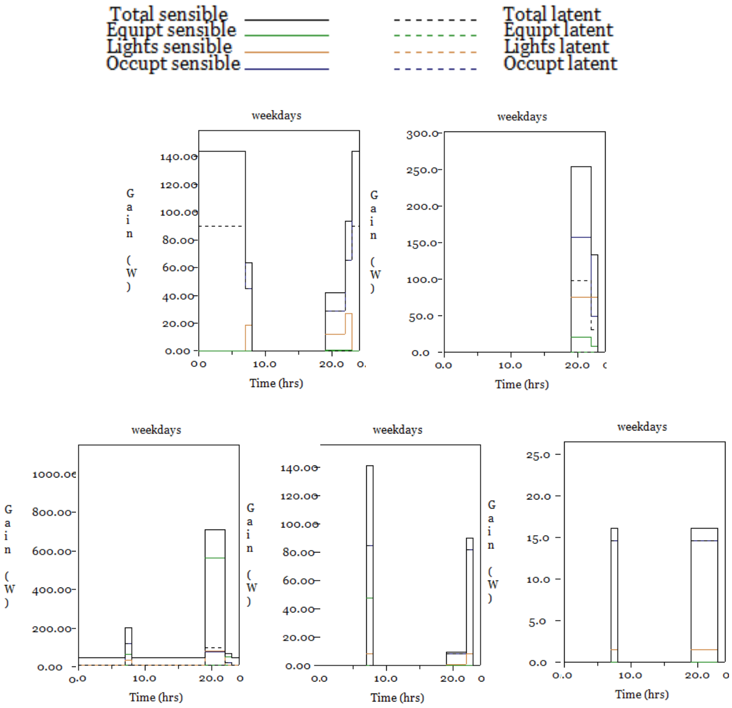

Figure C.2. Example of an indoor heat gains pattern for all the rooms during weekdays for apartment 1F (for bedrooms, living room, kitchen, WC and hall, respectively).

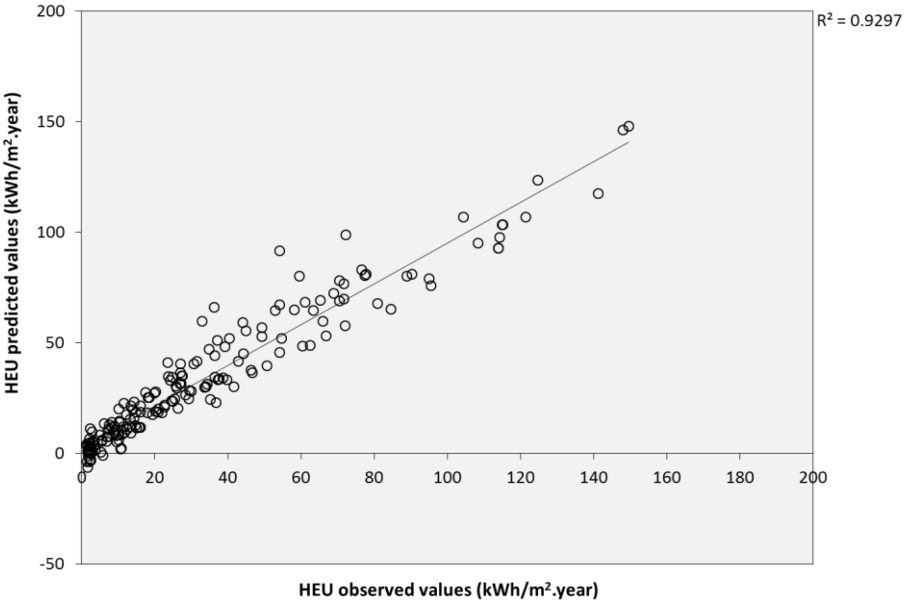

Figure C.3. Comparison between predicted values and observed values for the universal model developed to predict HEU (first approach), using the MNLR statistical model.

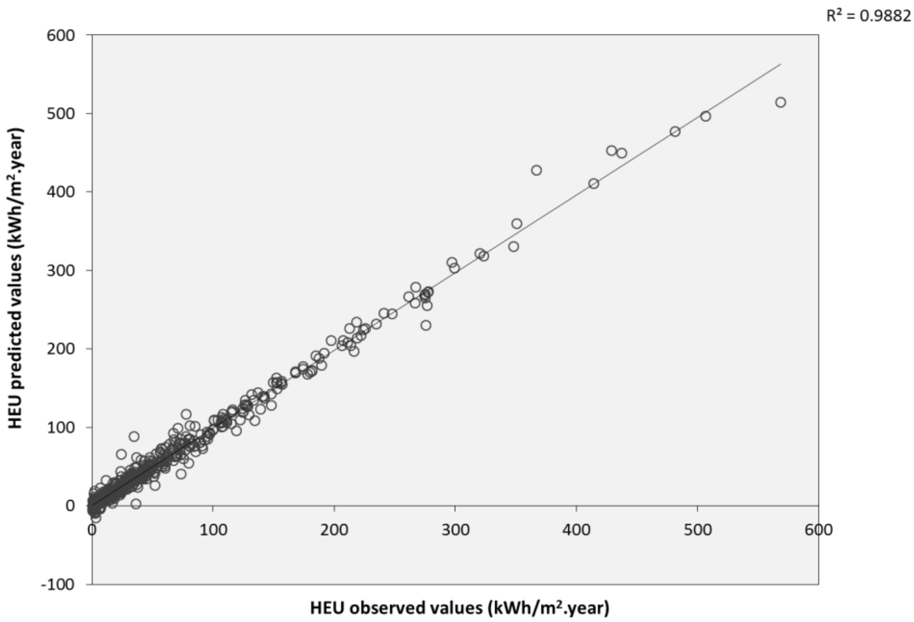

Figure C.4. Comparison between predicted values and observed values for universal model developed to predict HEU (second approach), using the ANN statistical model.

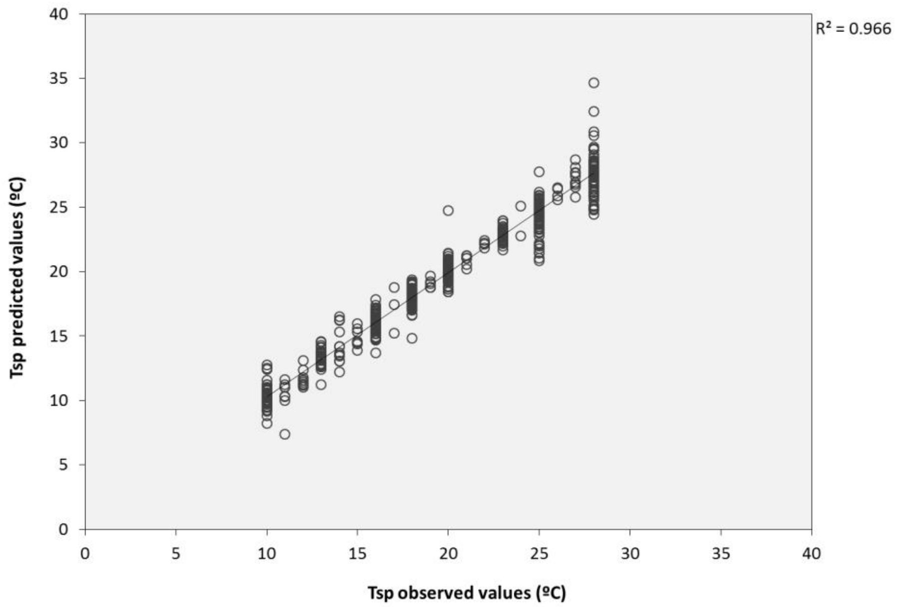

Figure C.5. Comparison between predicted and observed values for universal model developed to predict Tsp (second approach), using the ANN statistical model.

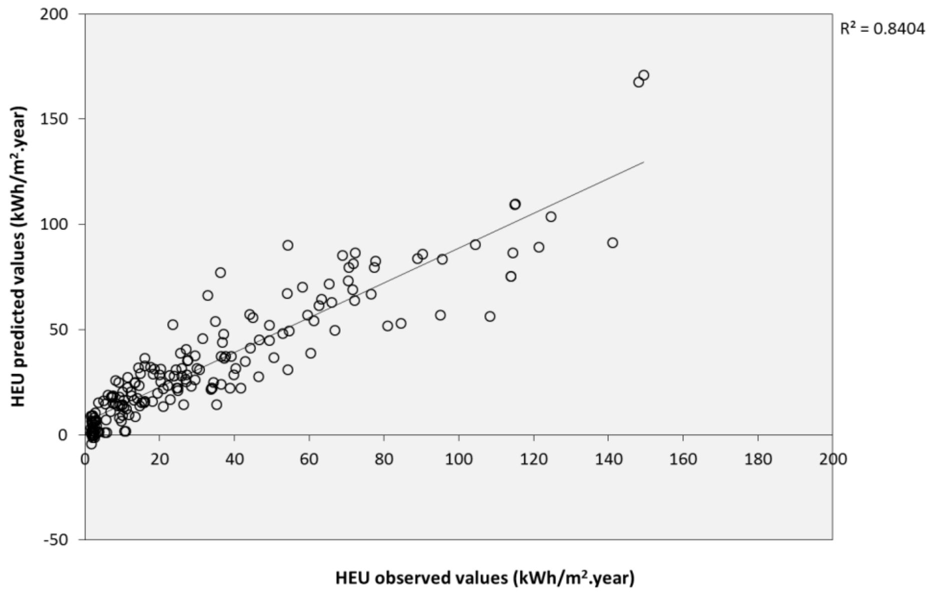

Figure C.6. Comparison between predicted and observed values for RCCTE specific model developed to predict HEU (first approach) using the MNLR statistical model.

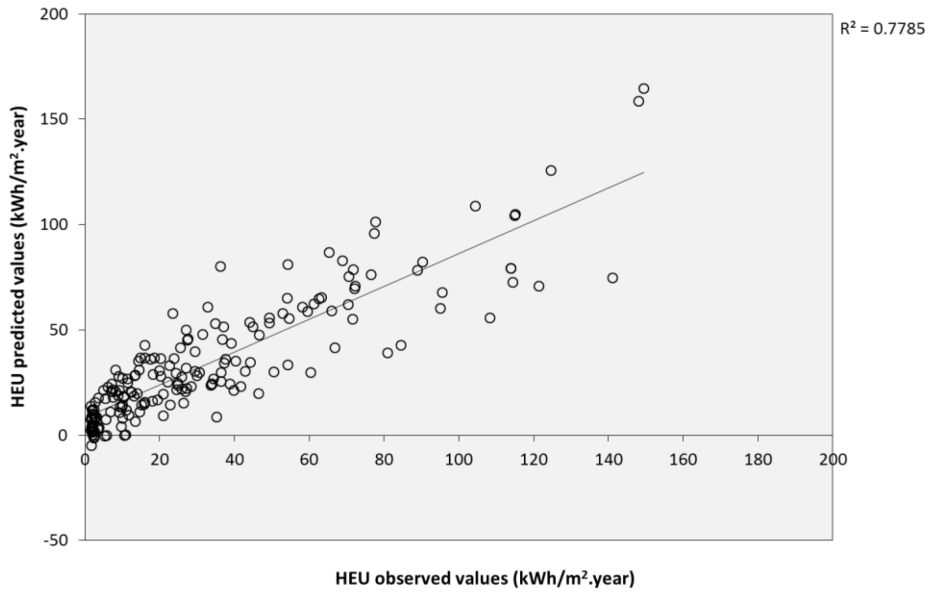

Figure C.7. Comparison between predicted and observed values for REH specific model develop to predict HEU (first approach) using the MNLR statistical model.

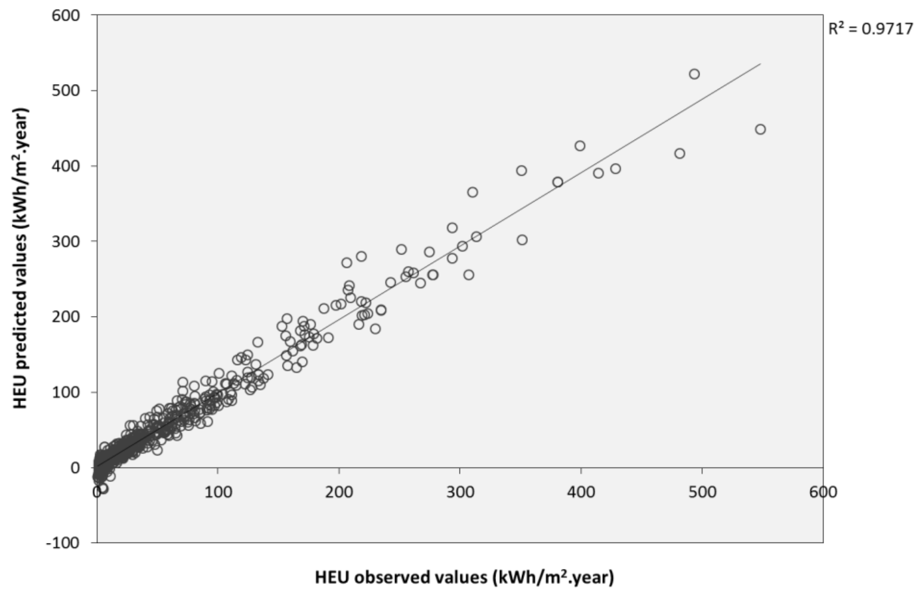

Figure C.8. Comparison between predicted and observed values for RCCTE specific model developed to predict HEU (second approach) using the ANN statistical model.

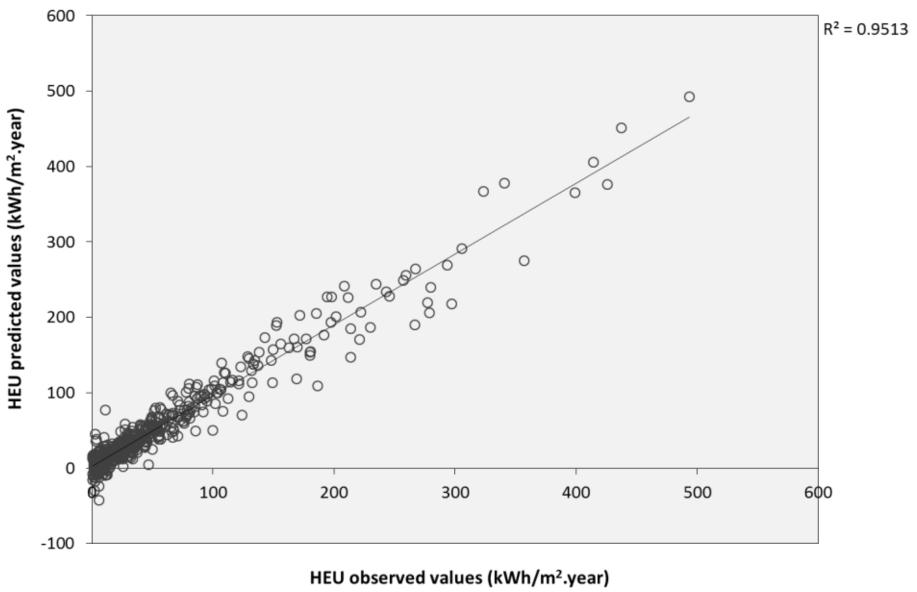

Figure C.9. Comparison between predicted and observed values for REH specific model developed to predict HEU (second approach) using the ANN statistical model.

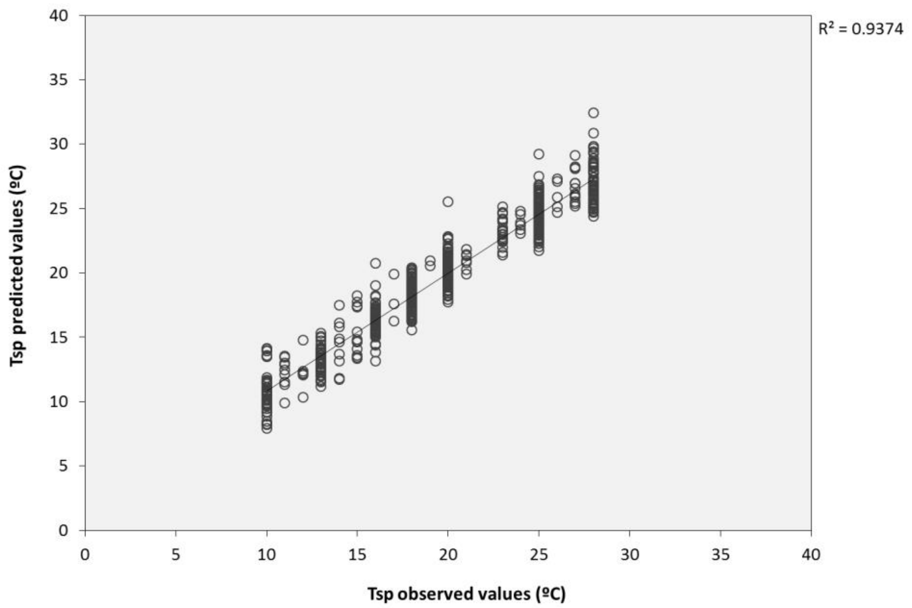

Figure C.10. Comparison between predicted and observed values for RCCTE specific model developed to predict Tsp (second approach) using the ANN statistical model.

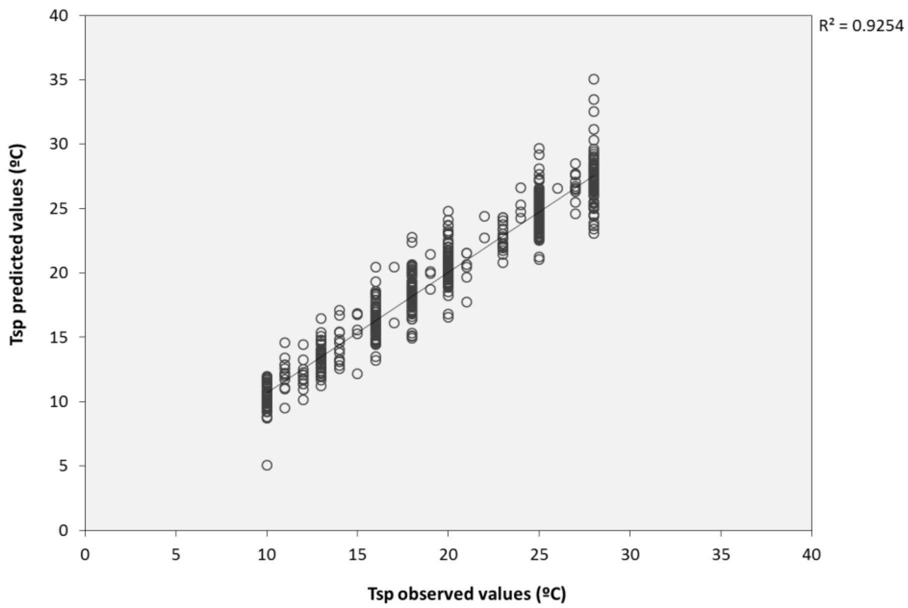

Figure C.11. Comparison between predicted and observed values for REH specific model developed to predict Tsp (second approach) using the ANN statistical model.

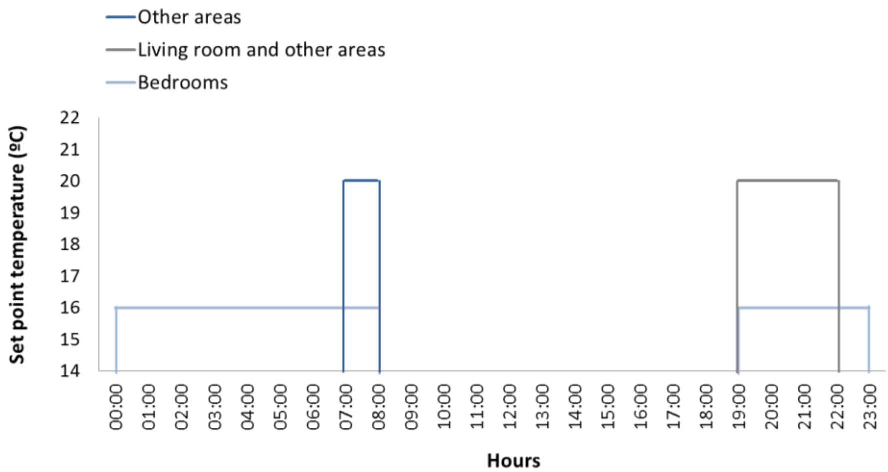

Figure C.12. Heating pattern for the weekdays.

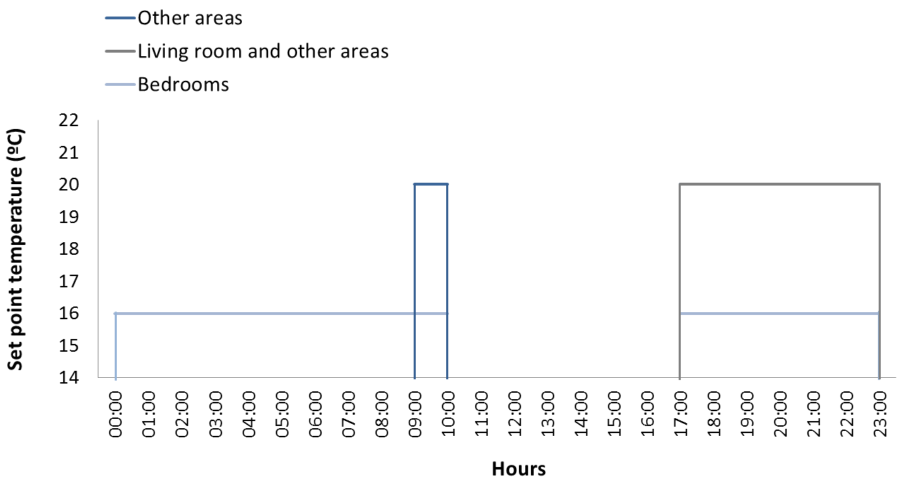

Figure C.13. Heating pattern for saturdays.

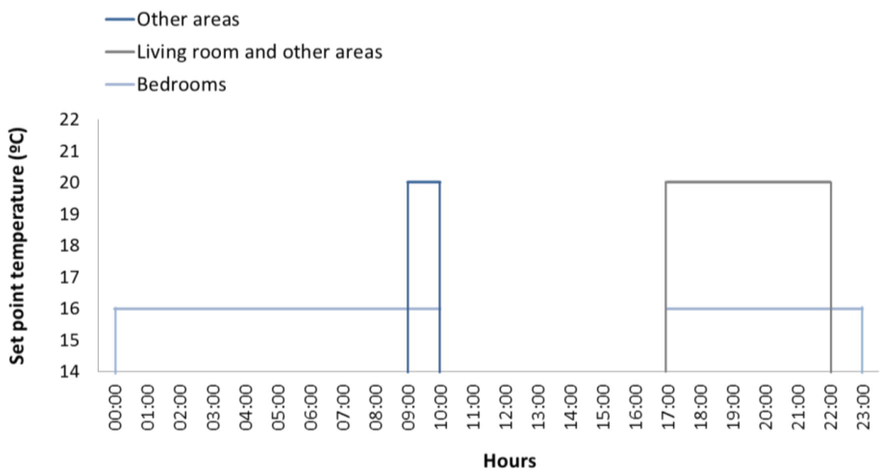

Figure C.14. Heating pattern for sundays.